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Integrated Synchromodal Transport Planning and Preference Learning

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Abstract

A comprehensive understanding of shippers' preferences can help transport freight forwarders create targeted transport services and enhance long-term business relationships. This research proposes an integrated approach to learn shippers' preferences in synchromodal transport operations and optimize transport services accordingly. A preference learning method was developed to capture shippers' preferences through pairwise comparisons of transport plans. To model the underlying complex nonlinear relationships and detect heterogeneity in preferences, artificial neural networks (NNs) were employed to approximate shippers' utility for a specific plan. Leveraging the learned preferences, a synchromodal transport planning model with shippers' preferences (STPM-SP) was proposed, with the objectives of minimizing the total transportation cost and maximizing shippers' satisfaction. A case study based on the European Rhine-Alpine corridor was conducted to demonstrate the feasibility and effectiveness of the proposed approach. The results demonstrated that artificial NNs have the capacity to identify complex (i.e., nonlinear and heterogeneous) relationships in shippers' preferences. The planning results showed that the STPM-SP effectively found solutions with a significant satisfaction improvement of 37%. This research contributes to learning shippers' preferences in the transport operation process and highlights the importance of incorporating these preferences into the decision-making process of synchromodal transport planning.

Keywords

freight systems, intermodal freight transport, optimization

Synchromodal transport is an emerging concept in logistics that evolved from intermodal transport (1, 2). It enables the flexibility to switch between available transport modes or routes (3), and can substantially reduce transportation costs, increase transportation efficiency, and promote emissions reductions. As the organizer and service provider of the transport system, freight forwarders respond to shipment requests, formulate transport plans, and assign transport tasks to carriers (4). The objectives of synchromodal transport operation commonly stem from the perspective of freight forwarders, such as minimizing total transport cost (5), total transport time (6), resource use (6), and CO_2 emissions (7). As the customers of the transport system, shippers play a key role in the real-world operation of transport systems. Shippers' expectations in relation to transport operations may differ from the goals of freight forwarders (8). For instance, the influence of cost on port choices varies between shippers and freight forwarders (9, 10). A comprehensive understanding of shippers' preferences would help freight forwarders create customized and targeted services that enhance customer satisfaction and loyalty. This would potentially lead to increased transport demand, higher revenue, and benefit long-term business relationships (11). However, only a few researchers have investigated the incorporation of shippers' preferences into the synchromodal transport operation (12, 13).

There are still challenges in relation to the acquisition and modeling of shippers' preferences. The traditional methods for studying shippers' preferences are based on

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Table 1. Models in the Recent Literature Together with their Considered Attributes

Research	Influential factors	Model	Specification
Nugroho et al. (31)	Cost, time, reliability, emissions	Mixed logit model	Linear
Kim et al. (17)	Cost, time, reliability, frequency	Latent class logit model	Linear
Khakdaman et al. (24)	Cost, time, reliability, flexibility	Multinomial logit model	Linear
Kurtuluş et al. (22)	Cost, time, reliability, frequency	Mixed logit model	Linear
Firdausiyah et al. (33)	Cost, time	Binary logit model	Linear
Nicolet et al. (34)	Cost, accessibility	Weighted mixed logit model	Linear
Román et al. (18)	Cost, time, reliability, frequency	Latent class logit model	Nonlinear
Jensen et al. (16)	Cost, time	Nested logit model	Nonlinear
Jourquin (35)	Cost, time, distance	Conditional logit model	Nonlinear
Feo-Valero and Martínez-Moya (8)	Cost, reliability, frequency	Mixed logit model	Nonlinear
Khakdaman et al. (32)	Cost, time, reliability, flexibility	Mixed logit model	Nonlinear
This study	Cost, time, delay, emission, transshipment	Preference learning	Model free

survey data. For example, shippers are asked to rate various transport attributes using a predefined scale of importance. However, this method has its limitations, including hypothetical bias (14) and challenges associated with large-scale survey data collection. The hypothetical nature of the survey may lead to responses that do not accurately reflect shippers' true preferences in practical situations. It could also be difficult for shippers to simultaneously assess various transport attributes and precisely describe to what extent they value a specific attribute. In addition, the inherent nonlinearity and heterogeneity in preferences call for powerful preference modeling tools (15–18). In this work, we refer to shipper preference heterogeneity as the variation in how shippers value different transport plan attributes. For instance, some shippers may opt for longer-duration plans for lower costs, whereas some may prioritize shorter lead times. Nonlinearity in preferences refers to the nonlinear relationship between transport attributes and the overall utility of a transport plan. With the advances in data collection techniques, it is important to design preference learning methods that can leverage large datasets and automatically capture complex relationships from data.

To this end, we proposed a preference learning model to estimate shippers' preferences from their actual decisions on transport services. A synchromodal transport planning model with shippers' preferences (STPM-SP) was developed, with the two objectives of minimizing the total cost and maximizing the shippers' satisfaction. The model was solved using a modified heuristic algorithm based on the adaptive large neighborhood search (ALNS), proposed by Zhang et al. (2). A case study was conducted based on the European Rhine-Alpine corridor to demonstrate the feasibility and effectiveness of the proposed method. The results showed that the proposed model can provide win–win solutions for both shippers and freight forwarders, leading to better resource utilization and service quality for the synchromodal transport system.

Literature Review

We reviewed relevant literature on (i) shippers' preferences, (ii) machine learning in transport choice analysis, and (iii) preference integration in intermodal transport planning. The research gaps are identified and discussed.

Shippers' Preferences

Extensive investigations have been conducted to identify the key attributes that affect shippers' satisfaction with transportation services. In general, transport cost, time, and reliability are considered to be the three core factors influencing the transport decisions of shippers (19, 20). Transport cost is listed as the major critical factor in several studies (21, 17). Kurtuluş et al. found that reducing transit time by 50% could increase the share of rail from 11% to 30% considering short-distance inland transport in Turkey (22). Reliability can be defined as the percentage of on-time delivery of freight/goods at the destination (8, 23–25), and higher reliability appears to result in higher service quality and customer satisfaction (22). Other service attributes have been investigated as well, such as frequency (17, 25), flexibility (24), and risk of damage (11). A few researchers have investigated the impacts of gas emissions (26, 27) and transshipment (28–30). The companies with higher export volumes tend to be more aware of the impact of greenhouse gases on the environment (31). Research on transshipment showed that this option may increase cost-effectiveness by enhancing multimodal transportation and optimizing route and time scheduling (30). Table 1 presents the summary of the research on shippers' preferences. Note that Khakdaman et al.'s research that examined shippers' preferences at the operational level has greater relevance to our research (24, 32).

For data collection techniques, most of the discussed literature is based on stated preference data, in which the experiments involve presenting individuals with hypothetical transport scenarios and asking them to choose from two or more options, such as mode, route, or departure time (36, 37). However, one major criticism of stated preferences is hypothetical bias (14), that is, the decisions made in hypothetical settings may differ from those made in real-life situations. The sources and evidence of hypothetical bias are examined in detail in the literature (38, 39). On the contrary, revealed preferences are observed from actual choices made in real-world settings. Some research has combined revealed preferences and stated preferences for transport behavior analysis (40, 37).

For preference modeling, the discrete choice model is one of the most classical methods for capturing shippers' preferences. Based on the multinomial logit (MNL) model (41), research on intermodal transport choice modeling attempted to relax the predetermined structures and linear characteristics of underlying functions in MNL. This exploration leveraged the advantages of a mixed MNL (MMNL) model, a nested logit model, a weighted logit model, a conditional logit (CL) model, and a latent class MNL model. Another key approach employs multicriteria decision-analysis methods (27, 42, 43), which evaluate multiple criteria in decision-making processes. The Bayesian approach can be integrated into both discrete choice models (44) and multicriteria decision-analysis methods (43). By leveraging prior distributions, it has the potential to produce more accurate estimations (44). In addition, some researchers emphasize the model's capability to handle nonlinearity in preference modeling. Jourquin argued that incorporating nonlinearity in choice modeling provides more degrees of freedom for model estimation (35). Jourquin incorporated Box–Cox transformations in the CL model to overcome multicollinearity. Jensen et al. examined the marginally decreasing sensitivity of cost in the freight model and demonstrated the necessity of taking nonlinearity into account (16).

Machine Learning in Transport Choice Analysis

With the growing availability of data, leveraging data-driven methodologies has emerged as a promising option for choice analysis. Data-driven approaches can identify behavioral patterns directly from the data (45), with fewer assumptions and predefined specifications compared with traditional statistical-based models. An artificial neural network (NN) is a type of machine learning model that uses interconnected layers of nodes to map from inputs to outputs. The multilayer structure and use of a nonlinear activation function enable NNs to approximate continuous nonlinear function (46). NNs and NN-based models have demonstrated notable predictive capability in travel behavior studies (47–49). Sifringer et al. proposed hybrid learning-based logit models in which the systematic utility consists of an interpretable part and a nonlinear part derived from NNs (48). They suggested that the proposed model can achieve better predictive performance and accuracy in parameter estimation, whereas MNLs that ignore these nonlinearities suffer a severe underfitting problem. Wang et al. proposed a deep NN architecture with alternative-specific utility functions (50). The results showed that the proposed model appeared to have a lower loss value in predicting the choice of trip purposes, outperforming several discrete choice models including binary logit, binary mixed logit, MNL, and MMNL models. Lee et al. compared the predictive capability of artificial NNs with MNL models based on a survey dataset with 4,764 observations (47). The cross-validation results showed that NN models outperform MNL models, with prediction accuracies around 80% compared with 70% for MNL models.

Some researchers have demonstrated the capacity of NNs to handle large volumes of data and complex model specifications (49, 51, 50). Wong et al. proposed a ResLogit model with a residual component to capture unobserved preference heterogeneity in the choice process (49). In contrast to baseline MNL models, the proposed model had smaller standard errors and higher efficiency in parameter optimization. Hillel found that owing to utilizing the gradient descent algorithm in optimum searching, the feed-forward NN could be trained up to 200 times faster than nested logit models (51). Wang et al. examined the performance of NNs and discrete choice models with sample size variation and indicated that the advantage of using deep NNs would be amplified when the sample size is large (50). Current literature has demonstrated the benefits of NNs in the transport choice modeling field (52), and more investigations and discussions remain to be conducted. Few researchers have explored the efficiency of NNs in learning the underlying heterogeneity in choices.

Preference Integration in Intermodal Transport Planning

Freight forwarders and shippers are two primary stakeholders in intermodal transport planning. Numerous studies have established the goals of intermodal transport systems from the perspective of freight forwarders. The primary objective of freight forwarders in intermodal transport planning is considered to be minimizing transport cost, which is typically composed of transit cost, loading/unloading cost, and storage/inventory cost (53). Some additional costs might also be included in the configuration of the total cost, such as delay penalties (2), emissions-related costs (54), and nonfulfilment penalties (55). Rather than focusing on a single criterion, some research models the trade-offs between various objectives of system operators using multiobjective optimization (54, 56, 57). Zhang et al. considered the three objectives of total cost, delivery time, and reliability, and combined the ϵ-constraint method and the memetic algorithm for optimum searching (58). Baykasoğlu and Subulan explored transport solutions that compromised transport costs, transit times, and carbon emissions and compared the optimization results using multiobjective optimization approaches (59).

All these objectives represent the benefits to system operators. However, the interests of shippers and operators can diverge, leading to transport planning outcomes that may prioritize the operators' benefits but might not necessarily align with the preferences of shippers (12). Some studies have indicated that operators are more cost-sensitive than shippers (8, 60). Feo-Valero and Martínez-Moya found that the roles of carriers and shippers significantly affect the impact of transport cost on port choice decisions (8). The reason for this could be that transport operators generally work with a profit margin on the price to maintain the turnover and acquire new clients (8). Duan et al. demonstrated that incorporating shippers' heterogeneous preferences for time and reliability in service network design can effectively lower the generalized cost and enhance the overall service level (61).

Some researchers have incorporated shippers' preferences into the operational process. Shao et al. used a dominance-based rough set approach to derive decision rules and require shippers to select the most important one (12). The selected rule was then presented as a new constraint for the optimization problem. The process of operators consistently seeking input from shippers during each planning phase can be time-consuming. Similarly, shippers may encounter difficulties evaluating and comparing multiple transport attributes simultaneously. Zhang et al. applied fuzzy set theory and obtained preference information through shippers' vague expressions on the importance of attributes including cost, time, reliability, risk, and emissions (13). The preferences of shippers were set as constraints that ensured the calculated satisfaction was equal to or higher than the predefined benchmark. A potential problem is that the preference data on the importance of attributes could have a hypothetical bias, as shippers may behave differently in choosing transport services. Furthermore, the predefined benchmark of shippers' satisfaction used in constraints needs to be calibrated when applied in different problem settings.

Research Gap and Contributions

Shippers' preferences have been explored in their choices of transport modes (17, 19, 23, 62), terminals (8, 29, 31), and service providers (11). The stated preference method has been widely applied in previous research, although hypothetical biases may affect preference estimation. The current research reveals shippers' preferences by developing a preference learning method to capture complex preference information. We demonstrate this capability through synthetic data as a proof of concept. Furthermore, shippers and freight forwarders may have different preferences whereas traditional intermodal transport planning tends to only consider freight forwarders' objectives. This research bridges this gap by integrating shipper preference learning with synchromodal transport planning. The developed approach aims to enhance transport planning decision making, align transport services with actual shippers' preferences, and foster stronger, long-term relationships between shippers and freight forwarders.

Problem Description

The main research problem is the integrated synchromodal transport planning problem considering shippers' preferences. There are two subproblems: 1) the biobjective synchromodal transport planning problem with shippers' preferences, and 2) the shippers' preference learning problem.

The transport system was modeled with two types of stakeholder, a freight forwarder and shippers. The freight forwarder is the operator of the transport system who collects requests from shippers and assigns the resources of carriers to these requests. Note that for the cases in which shippers directly interact with carriers, the end user of the proposed model could be the carriers. We assumed a steady market such that there are no new shippers entering during each optimization instance. The synchromodal transport planning problem focuses on finding Pareto solutions that optimize both the transport cost and shippers' satisfaction based on the captured preferences. Specifically, a request, $r \in R$, is to transport containers from the origin to the destination, meeting the requirements of shippers. The information of a shipment request includes the pickup terminal, p_r, the delivery terminal, d_r, pickup time window, $[a_{p_r}, b_{p_r}]$, delivery time window, $[a_{d_r}, b_{d_r}]$, and the number of containers, q_r. Multiple transport modes can be used and transshipment is allowed during the transport operation.

Preference learning in this case aimed to find out how transport choices are made by shippers. Knowing the underlying behavior of the shipper allows the freight forwarder to provide better services accordingly (13). This research simulated shippers' rankings on alternative plans provided by the freight forwarder and then used these to infer their preferences. We assumed that the freight forwarder is aware of the factors in transportation plans that influence shippers' preferences. The challenges lie in the model's capacity to learn complex relations between these transport factors and utilities for shippers, and acknowledging that shippers' preferences can be heterogeneous. It can be difficult to detect the nonlinear relations between transport attributes and utilities for shippers. Conventional statistical methods have been widely used to capture shippers' preferences, however, prior experiments are required, and inappropriate model specifications can affect estimation performance. In addition, shippers may exhibit heterogeneous preferences, which can be attributed to variables such as the type of cargo or the value and scale of the company. For instance, perishable goods may require a short shipping duration and high reliability; companies that prioritize eco-friendly shipping may choose sustainable transportation despite the associated higher costs. The presence of heterogeneous preferences also poses challenges for preference learning, as the model needs to discern variations in preferences based on shippers' decision making. Furthermore, actual shipping decisions may involve nonlinear trade-offs. For example, the desirability of transportation plans may experience exponential growth as transport costs decrease. The preference learning model should be capable of identifying these relationships through the training process.

Based on the description above, the assumptions are summarized as follows:

Assumption 1: It is assumed that the freight forwarder acts as the decision maker in the transport system. In situations where shippers directly interact with carriers, the shift of the decision-making role from the freight forwarder to the carriers does not affect the applicability of the proposed model.

Assumption 2: The freight forwarder is assumed to have essential transport network data, such as terminal locations, distances, vehicle information, and cost details, as well as complete information on shipper requests, covering pickup/delivery terminals, container quantities, and specified time windows. The freight forwarder is assumed to accommodate all received requests.

Assumption 3: It is assumed that shippers' satisfaction depends on five factors of the transport plans: transport cost, transport time, emissions, delay, and transshipment. Transport cost, transport time, and delay (or reliability) have been widely examined in previous research (8, 17, 21–25). Transshipment and emissions were additionally explored in some studies (26–30). Given the growing emphasis on sustainability and multimodal transport, this work also considers transshipment and emissions. The freight forwarder has no prior knowledge of the relationship between these factors and the utility of shippers. When shippers rank transport plans, they will make rational choices to maximize their utility.

Assumption 4: It is assumed that there are four characteristics in true shipper preferences to be considered: linearity/nonlinearity and homogeneity/heterogeneity. Linearity/nonlinearity implies a linear/nonlinear relation between attributes and utility. Homogeneity denotes uniform utility functions among shippers (Equations 42 and 43), whereas heterogeneity indicates varied attribute weights (i.e., coefficients) in the utility for different types of shippers (Equations 45 and 46).

As shown in Figure 1, this research proposes a general approach to integrating synchromodal transport planning and shippers' preferences. A mathematical planning model was developed to support synchromodal transport decision making considering the benefits to both freight forwarders and shippers. The preference learning model employs artificial NNs to estimate the utility function, which is then used to calculate the objective of the shippers' satisfaction. The proposed approach could be applied to intermodal transport systems involving multiple transport modes (i.e., air transport, maritime shipping, rail, and road freight). Freight forwarders should be able to generate alternative transport plans for shippers to evaluate, collect the choice data with shippers' consent, and utilize these data for preference learning. This approach allows freight forwarders to gain insights into shippers' preferences and propose tailored transport solutions, resulting in mutually beneficial outcomes for both freight forwarders and shippers.

Methodology

This section presents the mathematical models and algorithms for synchromodal transport planning and shipper preference learning. This study expands and builds on the authors' prior research (63). The notation is presented in Table 2. The values of parameters, such as the unit transport and loading cost for each mode, are listed in Table A1 in the Appendix.

Synchromodal Transport Planning

The proposed STPM-SP model had two objectives, minimizing the total cost and maximizing the shippers' satisfaction. The total transport cost (Z_c) consists of transit cost ($C^{transit}$), transfer cost ($C^{transfer}$), storage cost ($C^{storage}$), carbon tax ($C^{emission}$), waiting cost ($C^{waiting}$), and delay penalty (C^{delay}). Transfer cost is the sum of terminal transfer cost and pickup/dropoff transfer cost. Storage cost includes the storage time at pickup and

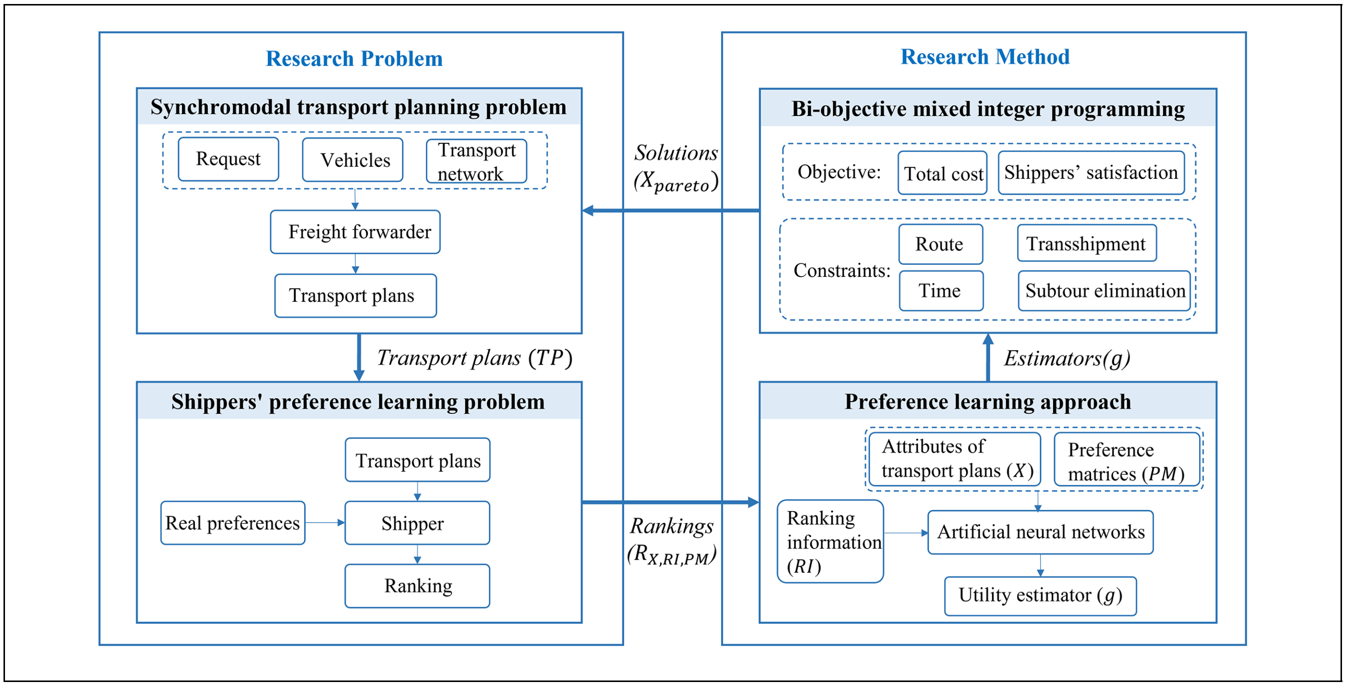

Figure 1. Research framework.

Table 2. Notation

Symbol	Description
Sets	
R	Set of requests indexed by r
S	Set of shippers indexed by s
K	Set of vehicles indexed by k and l
K_r	Set of vehicles serving request r
K^b	Set of barges indexed by k
K^t	Set of trains indexed by k
N	Set of terminals indexed by i
T	Set of transshipment terminals indexed by i
Parameters	
c_k^t	Unit transport cost using vehicle k; unit: euro/km/TEU
c_k^l	Unit loading (or unloading) cost using vehicle k; unit: euro/TEU
c_k^s	Unit storage cost using vehicle k; unit: euro/h/TUE
c_k^w	Unit cost of waiting time using vehicle k; unit: euro/h/TEU
c_k^e	Unit cost of emission tax using vehicle k; unit: euro/kg
c_r^d	Unit delay penalty for request r; unit: euro/h/TEU
dis_{ijk}	Distance between terminal i and j using vehicle k; unit: km
dis_r	Distance traveled for the request r; unit: km
v_k	Speed of vehicle k; unit: km/h
s_k	Starting depots of vehicle k
e_k	Ending depots of vehicle k
u_k	Capacity of vehicle k; unit: TEU
em_k	Emissions of vehicle k; unit: kg/(km · TEU)
q_r	Transport load of request r; unit: TEU
p_r	Pickup terminal of request r
d_r	Delivery terminal of request r;
$[a_{p_r}, b_{p_r}]$	Pickup time window of request r
$[a_{d_r}, b_{d_r}]$	Delivery time window of request r
tr_s	Parameter for scaling tr_r, $tr_s = 10$
X_r	Attributes of the transport plan for request r

(continued)

Table 2. (continued)

Symbol	Description
θ_r	Parameters of the preference learning model
Variables	
x_{ijk}	Binary variable; 1 if vehicle k uses the route between terminal i and j
y_{ijkr}	Binary variable; 1 if request r transported by vehicle k uses the route between terminal i and j
z_{ijk}	Binary variable; 1 if terminal i precedes terminal j in the route of vehicle k.
f_{iklr}	Binary variable; 1 if request r is transferred from vehicle k to vehicle l at transshipment terminal i
t_r^d	The delay time for request r; unit: h
t_{ikr}^l	Loading time for request r to vehicle k at the terminal i; unit: h
t_{ikr}^{arr}	Arrival time of request r served by vehicle k at terminal i; unit: h
t_{ikr}^{ss}	Service start time of request r served by vehicle k at terminal i; unit: h
t_{ikr}^{se}	Service finish time of request r served by vehicle k at terminal i; unit: h
t_{ik}^{arr}	Arrival time of vehicle k at terminal i; unit: h
t_{ik}^{dep}	Departure time of vehicle k at terminal i; unit: h
t_{ik}^{wait}	Waiting time of vehicle k at terminal i; unit: h
$c_r^{transit}$	Transit cost of request r; unit: euro
$c_r^{transfer}$	Transfer cost of request r; unit: euro
$c_r^{storage}$	Storage cost of request r; unit: euro

Note: TEU = 20-ft equivalent unit.

transshipment terminals. The emissions calculation follows an activity-based approach introduced by Demir et al., which considers factors such as vehicle type, distance traveled, and the number of containers (54). The delay penalty is associated with the load and delay time.

$$\min Z_c = C^{transit} + C^{transfer} + C^{storage} + C^{emission} + C^{waiting} + C^{delay} \tag{1}$$

$$C^{transit} = \sum_{k\in K}\sum_{r\in R}\sum_{i,j\in N} c_k^t q_r dis_{ijk} x_{ijk} \tag{2}$$

$$C^{transfer} = \sum_{k,l\in K}\sum_{r\in R}\sum_{i\in N}\left(c_k^l + c_l^l\right) q_r f_{iklr} + \sum_{k\in K}\sum_{r\in R}\sum_{i\in N} c_k^l q_r \left(y_{p_r ikr} + y_{id_r kr}\right) \tag{3}$$

$$C^{storage} = \sum_{k,l\in K}\sum_{r\in R}\sum_{i\in N} c_k^s q_r f_{iklr}\left(t_{ilr}^{ss} - t_{ik}^{se}\right) + \sum_{k\in k}\sum_{r\in R}\sum_{i\in N} c_k^s q_r y_{p_r ikr}\left(t_{p_r kr}^{ss} - a_{p_r}\right) \tag{4}$$

$$C^{emission} = \sum_{k\in k}\sum_{r\in R}\sum_{i\in N} c_k^e em_k q_r dis_{ijk} y_{ijkr} \tag{5}$$

$$C_{waiting} = \sum_{k\in K^b\cup K^t}\sum_{i\in N} c_k^w t_{ik}^{wait} \tag{6}$$

$$C_{delay} = \sum_{r\in R} c_r^d q_r t_r^d \tag{7}$$

The optimization model is designed to enhance the overall service performance by improving the aggregated satisfaction of shippers. Therefore, the second objective is to maximize the total satisfaction across all shippers. As shown in Equation 8, the total shippers' satisfaction (Z_s) is the sum of the satisfaction of each shipper. The estimated satisfaction of shipper r, denoted by $g(X_r, \theta_r)$, is determined by the attributes of transport plan $x_r = (c_r, t_r, dt_r, e_r, tr_r)$ and the parameters θ_r in the utility function. A transport plan, x_r, is characterized by transport cost, c_r, transport time, t_r, delay time, dt_r, emissions, e_r, and transshipment, tr_r, which can be calculated in unit terms by Equations 9 to 13. The transport cost, c_r, is the sum of transit cost, transfer cost, and storage cost for the request, r. In Equation 10, the transport time, t_r, is determined by the difference between the service end time of the request, r, at the delivery terminal and the service start time at the pickup terminal. When there is a delay, it is calculated by the difference between the service end time at the delivery terminal and the end of the time window, divided by the expected transport time. In Equation 13, tr_r measures the number of transshipments with a scale parameter, tr_s.

$$\max Z_s = \sum_{r\in R} g(x_r, \theta_r) \tag{8}$$

$$c_r = \frac{c_r^{transit} + c_r^{transfer} + c_r^{storage}}{dis_r q_r} \tag{9}$$

$$t_r = \frac{\sum_{k\in K_r}\left(t_{d_r kr}^{se} - t_{p_r rk}^{ss}\right)}{dis_r} \tag{10}$$

$$dt_r = \frac{\max\left(0,\ t^{se}_{d_r r} - b_{d_r}\right)}{\sum_{k \in K_r}\left(b_{d_r} - a_{p_r}\right)} \tag{11}$$

$$e_r = \frac{\sum_{k \in K_r} \sum_{i,j \in N} e_k y_{ijkr} q_r dis_{ijk}}{dis_r q_r} \tag{12}$$

$$tr_r = \sum_{k,l \in K_r} \sum_{i \in T} \frac{f_{iklr} q_r}{tr_s} \tag{13}$$

Constraints were formulated for vehicle routing, transshipment operations, subtour elimination, and operation time restrictions. Constraints 14 to 18 are the routing constraints. Constraints 14 and 15 ensure that vehicles and requests start/end at designated starting/ending depots and pickup/dropoff locations. Constraints 16 to 18 ensure the flow conservation for both vehicles and containers. Constraint 19 is the capacity constraint. Constraint 20 indicates that vehicle k is marked as "used" when there is at least one request transported by vehicle k between terminals i and j.

$$\sum_{i \in N} x_{s^k ik} = \sum_{i \in N} x_{ie^k k} \leq 1 \ \ \forall k \in K^b \cup^{K^t} \tag{14}$$

$$\sum_{k \in K} \sum_{i \in N} y_{p_r ikr} = \sum_{k \in K} \sum_{i \in N} y_{id_r kr} \leq 1 \ \forall k \in K, \forall r \in R \tag{15}$$

$$\sum_{j \in N} x_{ijk} = \sum_{j \in N} x_{jik} \ \forall k \in K^b \cup K^t, \forall i \in (N \setminus (s_k \cup^{e_k})) \tag{16}$$

$$\sum_{j \in N} y_{ijkr} = \sum_{j \in N} y_{jikr} \forall k \in K, \forall r \in R, \forall i \in (N \setminus (T \cup s_k \cup e_k)) \tag{17}$$

$$\sum_{k \in K} \sum_{j \in N} y_{ijkr} = \sum_{k \in K} \sum_{j \in N} y_{jikr} \ \ \forall r \in R, \forall i \in T \tag{18}$$

$$\sum_{r \in R} q_r y_{ijkr} \leq u_k x_{ijk} \ \ \forall k \in K, \forall (i,j) \in N \tag{19}$$

$$y_{ijkr} \leq x_{ijk} \ \forall k \in K, \forall r \in R, \forall (i,j) \in N \tag{20}$$

Constraint 21 ensures that transshipments take place only once per transshipment terminal. Constraint 22 prohibits transshipment between the same vehicle.

$$f_{ilkr} \leq 1 \ \forall (l,k) \in K, \forall r \in R, \forall i \in T \tag{21}$$

$$f_{ikkr} = 0 \ \forall k \in K, \forall r \in R, \forall i \in T \tag{22}$$

Constraints 23 to 26 are the subtour elimination constraints.

$$x_{ijk} \leq z_{ijk} \ \forall k \in K^b \cup K^t, \forall (i,j) \in N \tag{23}$$

$$z_{ijk} + z_{jik} = 1 \ \forall k \in K^b \cup K^t, \forall (i,j) \in N \tag{24}$$

$$z_{ijk} + z_{jpk} + z_{pik} \leq 2 \tag{25}$$

$$\forall k \in K^b \cup K^t, \forall (i,j), p \in N \tag{26}$$

Constraints 27 to 32 are the temporal constraints. Constraints 27 to 31 depict the relations of the arrival time, the service start time, and the service end time of requests, and the arrival time and departure time of vehicles. M is an extremely large positive value. Constraint 32 sets the time constraints for transshipment. Constraints 33 and 34 define the binary variables.

$$t^{arr}_{ikr} \leq t^{ss}_{ikr} \leq t^{se}_{ikr} \ \forall k \in K, \forall r \in R, \forall (i,j) \in N \tag{27}$$

$$t^{ss}_{ikr} + t^{l}_{ikr} \sum_{j \in N} y_{ijkr} \leq t^{se}_{ikr} \quad \forall k \in K, \forall r \in R, \forall (i,j) \in N \tag{28}$$

$$t^{arr}_{ik} \leq t^{arr}_{rik} \ \ \forall k \in K, \forall r \in R, \forall (i,j) \in N \tag{29}$$

$$t^{se}_{ikr} \leq t^{dep}_{ik} \ \forall k \in K, \forall r \in R, \forall (i,j) \in N \tag{30}$$

$$M\left(x_{ijk} - 1\right) \leq t^{dep}_{ik} + t_{ijk} + t^{arr}_{jk} \leq M\left(1 - x_{ijk}\right) \quad \forall k \in K, \forall (i,j) \in N \tag{31}$$

$$t^{dep}_{ikr} - t^{se}_{ilr} \leq M(1 - x_{iklr}) \quad \forall (k,l) \in K, k \neq l, \forall r \in R, \forall i \in T \tag{32}$$

$$x_{ijk} \in \{0,1\} \ \ \forall k \in K, \forall (i,j) \in N \tag{33}$$

$$y_{ijkr} \in \{0,1\} \ \forall k \in K, \forall r \in R, \forall (i,j) \in N \tag{34}$$

This research used a synchromodal transport planning model without shippers' preferences (STPM) as the benchmark model. The difference between the STPM-SP and STPM is that the latter is a single-objective optimization model not requiring knowledge of shippers' preferences (2). The objective of the STPM was to minimize the total cost (in Equation 2), and the constraints were the same as those of the STPM-SP.

Preference Learning

The preference learning model, denoted as $g(x, \theta) : X \rightarrow \hat{U}$, maps transport- and shipper-related inputs, X, to the estimated utility, $\hat{U}$, associated with a given transport plan, where θ represents the model parameters. Specifically, we used a five-layer artificial NN with the dimension $64 \times \times 64$ in the hidden layers (in Equation 35). Rectified linear units were employed as the activation function, ψ, which can be written as Equation 36. The ultimate output of the network is the estimated utility.

$$x_i = \psi(w_i x_{i-1} + b_i), \ \ (i-1, i) \in I \tag{35}$$

$$\psi(x) = \max(0, x) \tag{36}$$

where x_i and x_{i-1} represent the output and the input of layer i, respectively. The model input is the input of the first layer x_0; (w_i, b_i) are the learned weights and learned bias term of layer i; and I represents the set of layers.

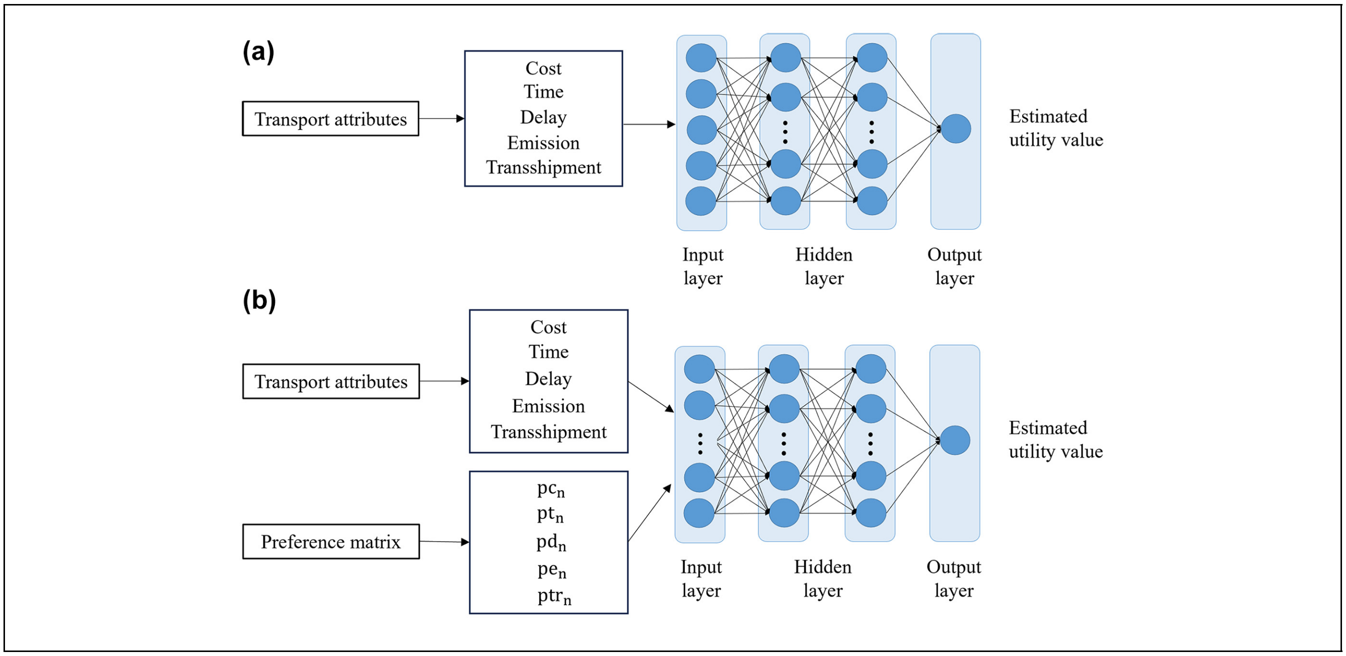

Figure 2. Structure of the proposed models: (*a*) neural networks, and (*b*) neural networks with preference matrix.

We developed two learning models for shippers' preference learning: artificial NNs for homogeneous preference learning and artificial NNs with preference matrix (NN-PM) for heterogeneous preference learning. As shown in Figure 2, both models utilized the artificial NN structure, the output being the utility of specific transport plans. The inputs of the NNs were the attributes associated with the transport plans. NN-PM incorporates both the transport plan attributes and the preference matrix of the shipper. The preference matrix was constructed based on shippers' previous choices and the comparison of transport attributes in these choices (in Equation 37), which can reflect the preferences of different shippers and enable more personalized utility estimation.

$$PM_n = [pc_n, pt_n, pd_n, pe_n, ptr_n] \tag{37}$$

where PM_n represents the preference vector for shipper n; and $pc_n, pt_n, pd_n, pe_n, ptr_n$ are the count number for the five transport attributes, respectively. Using the historical choice data, when the chosen transport plans have a lower value for a specific attribute, the corresponding count number will increase by 1, otherwise, it will decrease by 1.

The binary logit (BL) model was used as the baseline model. In a pairwise comparison between transport plan i and transport plan j, the utility of shippers toward each plan can be determined based on relevant factors (Equation 38), including cost, time, delay, emissions, and transshipment involved in the transportation process. Additionally, a random error was considered, following the Gumbel distribution. The probability of choosing transport plan i over transport plan j can be determined by Equation 39. BL models were established and trained using Biogeme 3.11 on Python.

$$u_i = \beta_c c_i + \beta_t t_i + \beta_e e_i + \beta_d d_i + \beta_{tr} tr_i + \epsilon_i \tag{38}$$

$$p(i) = \frac{e^{u_i}}{e^{u_i} + e^{u_j}} \tag{39}$$

Synthetic Preferences. This research used synthetic preferences to simulate shippers' ranking on alternative transport plans. Synthetic data offer flexibility for experiments, enabling the simulation of "what if" scenarios for shippers' preferences. This allowed for the evaluation of the proposed models across various preference settings, including homogeneity, heterogeneity, linearity, and nonlinearity. The relation in Equation 40 was used for the justification of their choices on two alternative transport plans (λ_i, λ_j). It was assumed that shippers would choose the transport plan with a higher utility value (8, 23).

$$\lambda_i \succ \lambda_j \Leftrightarrow U(\lambda_i) > U(\lambda_j), \tag{40}$$

where $U(\lambda_i)$ and $U(\lambda_j)$ represent the utilities of alternatives i and j, respectively.

The utility of each alternative, i, was composed of a systematic utility, V_i, and a random utility, ϵ_i (in Equation 41). Systematic utility functions can be categorized into linear and nonlinear forms. The linear form has been extensively utilized in previous research (23). As the impacts of transport cost and time on the utility may not be continuous and may exhibit a damping effect, piecewise and logarithmic specifications can be an option to capture varying or diminishing sensitivity at different levels of these attributes. We refer to the work of Jensen et al., as shown in Equation 43 (16).

Both linear and nonlinear utility functions in Equations 42 and 43 were used (separately) to generate the synthetic preferences to simulate shippers' choices.

$$U_i = V_i + \epsilon_i \tag{41}$$

$$V_i^1 = \beta_c c_i + \beta_t t_i + \beta_e e_i + \beta_d d_i + \beta_{tr} tr_i \tag{42}$$

$$V_i^2 = \beta_c F(c_i) + \beta_t F(t_i) + \beta_e e_i + \beta_d d_i + \beta_{tr} tr_i \tag{43}$$

$$F(x) = \begin{cases} \ln(x)^3 & \text{if } 0 < x \leq c_1 \\ a_1 \ln(x)^2 + b_1 & \text{if } c_1 < x \leq c_2 \\ a_2 \ln(x) + b_2 & \text{if } c_2 < x \end{cases} \tag{44}$$

In Equation 44, the values of c_1, c_2, a_1, b_1, b_2 align with those in the research of Jensen et al. (16). The connectivity and continuity of the cost curve were demonstrated in the work of Rich (64).

Shippers' preferences can exhibit heterogeneity in real life, that is, shippers typically have different prioritizations for transport attributes. To represent the prioritization, we assumed different shipper classes with different weights assigned to transport attributes (i.e., α_c, α_t, α_e, α_d, α_{tr}). The heterogeneous systematic utility in linear functions and nonlinear functions can be written as follows:

$$\begin{aligned} V_i^{h1} &= \alpha_c \beta_c c_i + \alpha_t \beta_t t_i \\ &\quad + \alpha_e \beta_e e_i + \alpha_d \beta_d d_i + \alpha_{tr} \beta_{tr} tr_i \end{aligned} \tag{45}$$

$$\begin{aligned} V_i^{h2} &= \alpha_c \beta_c F(c_i) + \alpha_t \beta_t F(t_i) \\ &\quad + \alpha_e \beta_e e_i + \alpha_d \beta_d d_i + \alpha_{tr} \beta_{tr} tr_i \end{aligned} \tag{46}$$

Evaluation Criteria. To evaluate the predictive performance of the model, we applied the model to the test dataset and used the prediction accuracy (in Equation 47) and the log loss (in Equation 48) as the evaluation criteria. Prediction accuracy was represented by the proportion of pairwise comparisons that were correctly predicted. The log-loss metric quantified the divergence between the predicted probability and the actual value. A higher log-loss value indicates a greater deviation between the predicted probabilities and the actual labels.

$$acc = 1 - \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|, \tag{47}$$

$$L = -\frac{1}{N} \sum_{i=1}^{N} (y_i \log(p) + (1 - y_i) \log(1 - p)), \tag{48}$$

where

$\hat{y}_i$ and y_i are predicted and true labels of shippers' choices, respectively;

N represents total number of tested pairwise comparisons; and

p is predicted probability that $y_i = 1$.

Solution Algorithms

Algorithm 1 was designed for preference learning based on shippers' feedback. The inputs of preference learning include shippers' ranking results, F, shippers' ID, S, transport plans, X, with attributes and the learning model with initialized parameters, $g(\theta_0)$. Parameters included the epochs, ep, batch size, b, and learning rate, lr, for the training of NNs. The output is the trained parameters of the NN, $\theta_{current}$. Before the model-training process, shippers' ranking feedback, F, is transformed into pairwise comparisons.

The task of training was to optimize parameters such that the preference learning model could accurately

Algorithm 1 Preference learning algorithm

Require: $F, S, X, lr, ep, b, g(x, \theta_0)$

Initialize θ_0

for $i \leftarrow 1, n$ **do**

$[x_i, x_j, y] \leftarrow transformation(X, F, S, i)$ ▷ Transform to pairwise comparison

$\hat{u}_i \leftarrow g(x_i, \theta_n)$, $\hat{u}_j \leftarrow g(x_j, \theta_n)$

if $\hat{u}_i > \hat{u}_j$ **then**: $\hat{y} \leftarrow 1$ ▷ Choose x_i over x_j

else: $\hat{y} \leftarrow 0$ ▷ Choose x_j over x_i

end if

$L_n = loss\_funtion(y, \hat{y}, \hat{u}_i, \hat{u}_j)$; ▷ Calculate the loss

$\frac{\partial L_n}{\partial \theta_n} = backpropagate(g(x, \theta_n), L_n)$; ▷ Calculate the gradient

$\theta_{n+1} = update\_parameters\left(\theta_n, \frac{\partial L_n}{\partial \theta_n}, lr\right)$ ▷ Update the utility predictor

end for

$\theta_{current} \leftarrow \theta_n$

estimate the shippers' utility of a specific transport plan. The utility estimations were expected to generate transport plan comparison results that would be consistent with the true comparison outcomes. The optimization of model parameters can be divided into three main steps: 1) estimating the utilities of transport plans (Line 4); 2) predicting choices and computing the loss (Lines 5 to 8); and 3) backpropagating and updating parameters (Lines 9 to 10). The transport attributes were the inputs of NNs for the utility estimation. In cases where there was heterogeneity, the preference matrix was used as an additional input to NN-PM. In each comparison between two transport plans, the learning model first computed the utility of each plan separately. Subsequently, the plan with the higher utility value was selected. The pairwise comparison results provided by shippers were then used to supervise the comparisons conducted based on the preference learning model. Considering the probabilistic nature of individual decision making (65–67), the cross-entropy loss was used to estimate the population error between the estimated shippers' choices and the true shippers' choices.

ALNS is a powerful heuristic algorithm to produce (near) optimal solutions for vehicle routing problems (2, 7, 13). In this research, Algorithm 2 was proposed for STPM-SP, which was extended from earlier research (2) and the differences were: 1) incorporating the shippers' satisfaction, $g(\theta)$, into the objective function; 2) assigning a higher acceptance probability to the solutions with better performance in relation to shipper satisfaction; and 3) searching for Pareto solutions considering shippers' preferences. The inputs of Algorithm 2 included vehicles (K), requests (R), terminals (N), iteration number (I) and the satisfaction estimator, $g(\theta_r)$. The outputs consisted of the Pareto solutions for STPM-SP (X_p). In the search for Pareto solutions, n_p denotes the label of the Pareto solutions: $n_p = 1$ means the current solution is a nondominated one and will be included in the Pareto set; X_{-x} represents the solution set excluding the solution, x. Details of operators used and the adaptive mechanism can be found in our previous research (2, 7, 13, 68).

Algorithm 2 ALNS algorithm with shippers' preferences

Require: $K, R, N, I, g(\theta_r)$
Ensure: X_{pareto}
1: obtain the initial solution $X_{initial}$; $X_{last} \leftarrow X_{initial}$; initialize Tem, R_{pool}, X_p
2: **for** $i \leftarrow 1, I$ **do**
3: Refresh weights and choose operators based on weights; $X_{current} \leftarrow X_{last}$
4: **while** R_{pool} is not empty **do**
5: $[X_{current}, R_{pool}] = RemovalOperator(X_{current}, R_{pool})$;

(continued)

Algorithm 2 (continued)

6: $[X_{current}, R_{pool}] = InsertionOperator(X_{current}, R_{pool})$
7: **end while**
8: **if** $c(X_{current}) < c(X_{last})$ and $U(X_{current}, g(\theta_r)) > U(X_{last}, g(\theta_r))$ **then**
9: $X_{last} \leftarrow X_{current}$
10: **else if** $c(X_{current}) < c(X_{last})$ and $U(X_{current}, g(\theta_r)) < U(X_{last}, g(\theta_r))$ **then**
11: **if** $\frac{c(X_{last}) - c(X_{current})}{c(X_{current})} < \frac{U(X_{last}, g(\theta_r)) - U(X_{current}, g(\theta_r))}{U(X_{last}, g(\theta_r))}$ **then**
12: $X_{last} \leftarrow X_{current}$
13: **else if** $c(X_{current}) > c(X_{last})$ and $U(X_{current}, g(\theta_r)) > U(X_{last}, g(\theta_r))$ **then**
14: **if** $\frac{c(X_{current}) - c(X_{last})}{c(X_{current})} > \frac{U(X_{current}, g(\theta_r)) - U(X_{last}, g(\theta_r))}{U(X_{last}, g(\theta_r))}$ **then**
15: $X_{last} \leftarrow X_{current}$
16: **else**
17: $X_{last} \leftarrow X_{current}$ with the probability $p = exp\left(\frac{U(X_{last}, g(\theta_r))}{U(X_{current}, g(\theta_r))} / Tem\right)$
18: **end if**
19: **end if**
20: **end if**
21: $X = X \cup X_{last}$
22: **end for**
23: **for** $x \in X$ **do**
24: $n_p = 1$
25: **for** $x' \in (X_{-x})$ **do**
26: **if** $c(x') < c(x)$ and $U(x', g(\theta_r)) > U(x, g(\theta_r))$ **then**
27: $n_p = 0$; *break*;
28: **end if**
29: **end for**
30: **if** $n_p = 1$ **then**
31: $X_p = X_p \cup {}^x$
32: **end if**
33: **end for**

Note: ALNS = adaptive large neighborhood search.

Case Study

The European Gateway Services (EGS) network, shown in Figure 3, was used to conduct the experiments for model evaluation. The EGS network is located along the Rhine-Alpine corridor, providing connections between the ports of Rotterdam, Antwerp, and the prominent economic hubs in Western and Central Europe. The instances comprised a total of 116 vehicles, including 49 barges, 33 trains, and 34 trucks. The specific parameters related to vehicles were set to those in the previous research (13). Note that for this case study, we considered three transportation modes (i.e., barge, train, truck). However, if additional transport modes are available, they could also be incorporated into the proposed model. Before transport planning, requests were generalized by randomly selecting the origin terminal, p_r, destination terminal, d_r, pickup window, $[a_{p_r}, b_{p_r}]$, dropoff window, $[a_{d_r}, b_{d_r}]$, and the load of

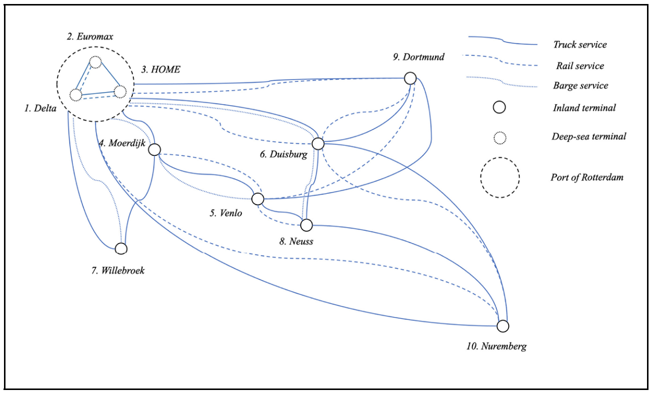

Figure 3. European Gateway Services network (5).

containers, q_r. The requests' origins and destinations were randomly distributed among deep-sea terminals and inland terminals, respectively. The container volumes of the requests were independently drawn from a uniform distribution with a range of 10 to 30 TEUs (20-ft equivalent units). Additionally, the earliest pickup time for the requests was independently drawn from a uniform distribution ranging from 1 to 120. The latest delivery time was determined by the earliest pickup time and the lead time, $b_{d_r} = a_{p_r} + LB_r$, with LB_r independently drawn from a uniform distribution with a range of 20 to 80 h.

Considering the characteristics of shippers'"true" preferences, four "what if" scenarios were designed with the specific utility functions (see Tables A2 and A3 in the Appendix):

- Homogeneous linear preferences scenario (HoS1): all shippers follow the linear utility functions;
- Homogeneous nonlinear preferences scenario (HoS2): all shippers follow the nonlinear piecewise specifications;
- Heterogeneous linear preferences scenario (HeS1): four shipper classes with different linear utility specifications;
- Heterogeneous nonlinear preferences scenario (HeS2): four shipper classes follow different nonlinear piecewise utility specifications.

For heterogeneous scenarios, Khakdaman et al. identified four shipper classes through latent class analysis, utilizing data obtained from an extensive survey conducted among global shippers (24). According to their findings, "high service-level shippers" make up 35.9% of the total, and "cost-sensitive shippers" account for 32.3%. In our study, we incorporated these two shipper classes and adapted the remaining two based on the transport attributes that are used in our study.

- Class 1: High service-level shippers (35.9%): the shippers look for improvements in service levels, particularly in minimizing time and delay;
- Class 2: Cost-sensitive shippers (32.3%): the shippers are sensitive to the cost. They are willing to take risks and more time for the cost reduction in return;
- Class 3: Eco-conscious shippers (18.4%): the shippers tend to minimize the environmental impact of their shipping activities;
- Class 4: Cost-efficient shippers (13.4%): the shippers tend to simultaneously minimize delays and costs in their shipping operations.

To collect the shippers' feedback data from preference learning, this research conducted 30 instances of synchromodal transport operations and simulated the ranking process of shippers using utility functions predefined with synthetic preferences. It was assumed there were 100 shippers in the system. In a single instance of planning, a shipper could have one or multiple requests or none. The freight forwarder received 100 to 200 requests. After receiving shipment requests, the freight forwarder used the STPM to propose transport plans (assigning vehicles and routes) for each request without consideration of shippers' preferences. To collect ranking information from the shippers, the freight forwarder selected several low-cost solutions. The transport plans within each solution were assigned to corresponding shippers with calculated transport attributes. Then, the freight forwarder asked shippers to rank the provided alternatives according to their preferences. The choices were simulated based on synthetic preferences and ranking transport alternatives based on respective utility values. As a result, the transport planning operations generated 4,777 transport plans after removing duplicates. After the simulation of shippers ranking the assigned transport plans, the ranking outcomes were structured into pairwise comparisons, resulting in over 100,000 pairs. We divided these data into training and testing datasets, comprising 70,000 and 30,000 samples, respectively. Across each scenario of shippers' preferences, experiments were conducted with varying training sample sizes.

Discussion

In the case study, we adopted both real-life intermodal transport information and synthetic shippers' preferences. We constructed the synthetic preferences in a way that informed the current understanding of shippers' preferences in the research field and ensured that the simulated scenario closely reflected real-world conditions. For the operational side, we adopted the operational scope and transport network of the real-world intermodal transport system, EGS (now Hutchison Ports Europe Intermodal) (69). The operational parameters (see Table A1 in the Appendix) were based on previous research (2, 5, 70). For the shipping demand, shippers' choices were simulated using synthetic preferences. We first assumed specific transportation attributes that influence shippers' preferences, as outlined in Assumption 3. Then the shippers' utility functions were constructed for the homogeneous scenarios. In the heterogeneous scenarios, we assumed there were four distinct groups of shippers, each with specific proportions, based on prior research (24). The preference matrix was directly derived from the observed choices of the shippers. It is important to note that if real preference data become available, it will be crucial to incorporate these into the model for further evaluation.

Results for Preference Learning

First, we will discuss the performance of preference learning methods under the above-mentioned scenarios.

Homogeneous Preferences. Figure 4, *a* and *b*, shows the accuracy and log-likelihood of the prediction results for BLs and NNs in the HoS1 scenario. In Figure 4*a* it can be observed that both BLs and NNs achieved an above 90% correct prediction, which improved slightly with the increase in sample size. The reason for the high prediction accuracy is that the BL had the correct model specification that matched the actual preferences, and NNs can also capture preferences. In addition, the NNs had a lower log loss with sample sizes of $7 \times 10^2, 7 \times 10^3, 7 \times 10^4$, which is in line with the results of Wang et al. (50). For the nonlinear case of HoS2, Figure 4, *c* and *d*, shows that as the sample size increased from 7×10^1 to 7×10^3, the NN prediction accuracy improved significantly, achieving 85% with 7×10^3 samples, whereas the BL accuracy remained below 60%. This was owing to the insufficient model specification of BL, which could not handle the nonlinearity in the data, whereas NNs can capture these nonlinear relationships. It should be noted that a relatively large sample size is required for NNs to capture nonlinearity, which was 7×10^3 in this case. Similar to HoS1, the NN log loss was lower than BL when the sample size was small, but it increased substantially as the sample size grew.

Heterogeneous Preferences. Under HeS1 with a heterogeneous yet linear utility specification, we compared three models where in addition to the BL and NNs, we also had NN-PM in which the preference matrix was incorporated. Figure 5, *a* and *b*, shows that all three models achieved an accuracy of over 80%. As the sample size increased, the accuracy of NN-PM increased to 90%, whereas the changes in the prediction accuracy of the BL and NNs were insignificant. This may be because, with the inputs of the preference matrix, artificial NNs can capture heterogeneity across shipper classes and construct utility functions that can predict new choices considering their respective preferences.

When the true preferences were nonlinear and heterogeneous under HeS2, Figure 5, *c* and *d*, displayed an accuracy below 60% for BL, as the model specification was incapable of capturing the nonlinearity and heterogeneity from the data. The accuracy of NN-PM was similar to NN when the sample size was 7×10^1, and it became higher than NN as the sample size increased. The log loss of NN and NN-PM had lower values than BL when the sample size was large ($7 \times 10^3, 7 \times 10^4$).

Discussion. An increase in sample size can generally decrease prediction errors, and artificial NNs are particularly sensitive to changes in sample size. This is because artificial NNs are designed to learn directly from data, without relying on predefined model specifications. It is important to note that the improvement in NNs slows as the sample size increases beyond a certain threshold. This threshold is related to various factors, including the input data and the underlying patterns of the sample data (50). For instance, in the case of the NN model, the sample size required to achieve a high performance would be dependent on the specific scenario and the shippers' actual preferences. Specifically, in HoS1 and HeS1, a high NN performance was achieved with a sample size of 7×10^2, and further increasing the sample size did not result in significant performance gains in either accuracy or log loss. However, in the HoS2 and HeS2 scenarios, the threshold value was found to be 7×10^3.

In addition, Scenario HeS1 revealed that artificial NNs with different inputs required different sample sizes to achieve optimal performance. It can be seen in Figure 4, *a* and *b*, that NNs achieved the best performance with a sample size of 7×10^2, whereas NN-PM required a larger sample size of 7×10^3. This difference can be explained by the incorporation of the information preference matrix making artificial NNs more effective in leveraging large datasets in scenarios where shippers' preferences were heterogeneous.

Results of Synchromodal Transport Planning

This section examines the performance of STPM-SP. The trained utility estimators were utilized during the planning process to assess the satisfaction of shippers in relation to transport solutions. The STPM was used as a benchmark model to compare the impact of integrating preference information on transport solutions. We conducted experiments in four scenarios (HoS1, HoS2, HeS1, HeS2) using STPM and STPM-SP. In total, there

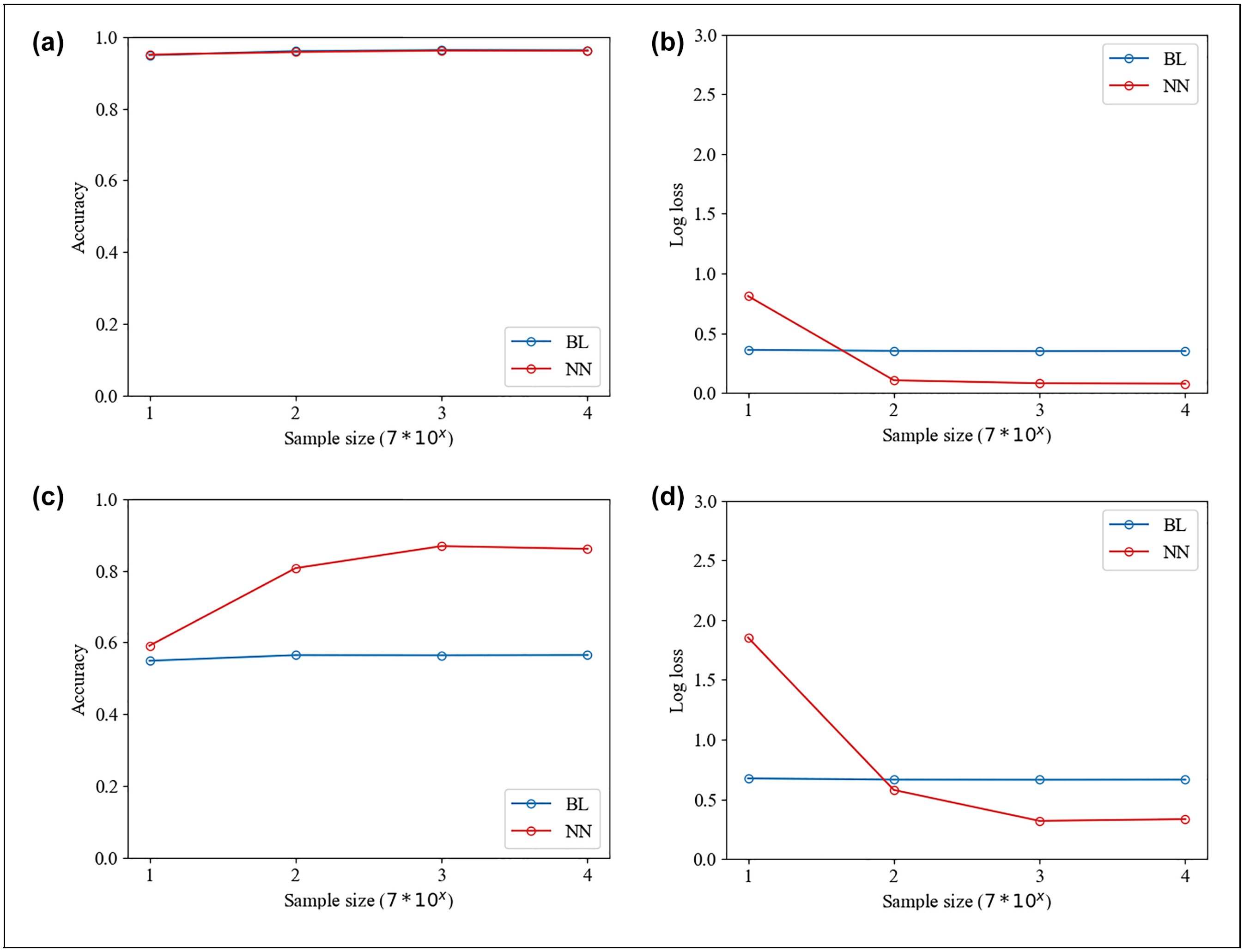

Figure 4. Evaluations of utility predictions: (*a*) HoS1 accuracy, (*b*) HoS1 log loss, (*c*) HoS2 accuracy, and (*d*) HoS2 log loss.

were 80 instances of synchromodal transport operations conducted by running five repetitions for each combination of preference scenario, planning model, and number of requests.

As shown in Table 3, utilizing the preference information led to a maximum 37% increase in shipper satisfaction, whereas the total cost experienced an average increase of 7% across repetitions. By comparing the solutions with the maximum satisfaction improvement and the solutions with the most cost-efficient satisfaction improvement (with the lowest relative cost improvement), it was observed that the most cost-efficient satisfaction tended to be approximately half the maximum satisfaction attained, which was about 19%, with only a 1% increase in cost.

In the scenarios in which all shippers shared the same preferences, the trade-offs between cost and shipper satisfaction appeared to be less cost-efficient compared with the scenarios with heterogeneous preferences. This can be explained as follows: when shippers' preferences diverge, freight forwarders have the flexibility to adjust the resource allocation across shippers instead of requiring additional resources for satisfaction improvement. By comparing the outcomes of different true model specifications, a notable trend was that satisfaction improvement was more significant in the nonlinear than the linear cases. This could be because the attribute changes in the nonlinear functions had a greater impact on satisfaction compared with the changes in linear functions. Therefore, the potential improvement in satisfaction was closely linked to the relationship between the actual utility and its factors. Nonlinear functions may amplify the effects of attribute changes, leading to more substantial improvements in satisfaction.

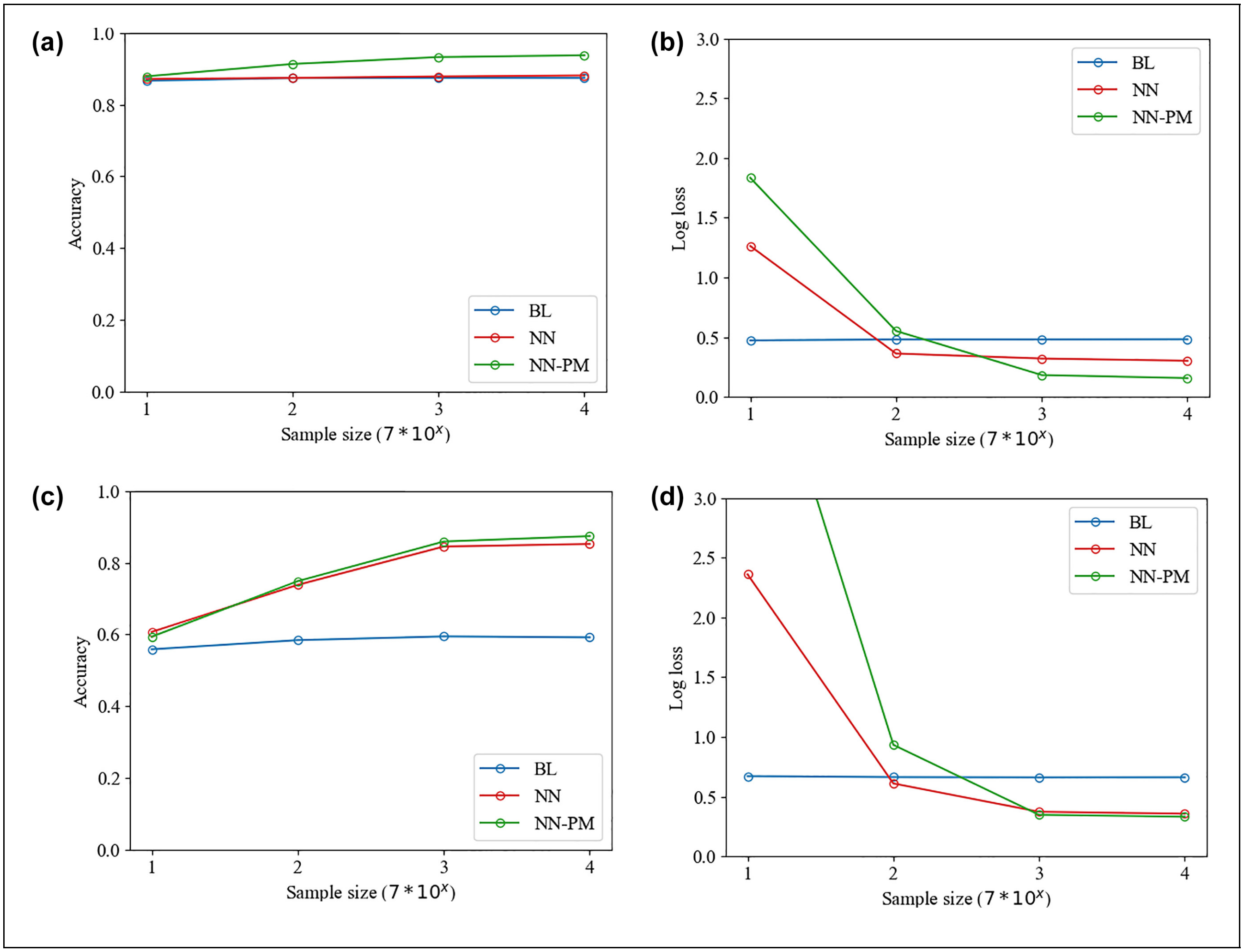

Figure 5. Evaluations of utility predictions: (*a*) HeS1 accuracy, (*b*) HeS1 log loss, (*c*) HeS2 accuracy, and (*d*) HeS2 log loss.

Further Analysis of Planning Results

To more elaborately evaluate the impact of STPM-SP on the satisfaction of shippers, we provide further results for the homogeneous and heterogeneous scenarios. For simplicity, we picked the linear utility specification to support our explanation.

Under homogeneous preferences, Figure 6 compares the solution attributes between the solution proposed by STPM (base solution) and the Pareto solution set with six nondominated solutions of STPM-SP on the same 100 requests. The Pareto set of nondominated solutions had a satisfaction improvement ranging from 18.72% to 26.98%. All of these nondominated solutions had higher generalized costs, transport costs, and emissions compared with the base solution. However, they also required shorter times, suggesting that shippers prioritized faster delivery over lower costs and emissions. Solution 1 (S1) had the largest satisfaction improvement (26.98%) among the nondominated solutions in the Pareto set. However, it also had the most significant increase in generalized cost, transport cost, and emissions compared with the base solution. In addition, trade-offs between different solution attributes were observed, for example, S2 and S1 had similar satisfaction ratings, but S2 had a lower increase in cost and emissions compared with S1, and reduced time and transshipment. However, the trade-off for this improvement was an increase in delay.

To better understand the influence of STPM-SP on the individual shipper, Figure 7 shows the average proportion of shippers with various levels of satisfaction improvement in the instances with 100 requests. A positive level (in red) indicates that the STPM-SP model improved the satisfaction levels of the shipper compared with the solution generated by the STPM model, otherwise, the value is negative (shown in blue). Figure 7 shows the performance variability for shippers. About

Table 3. Results of STPM and STPM-SP

	SI*, %	CI*, %	SI, %	CI, %
HoS1				
R10	10.937	14.475	2.699	0.707
R50	21.172	12.735	6.396	−0.348
R100	17.445	12.689	13.282	6.176
R150	47.671	8.277	25.087	2.216
HoS2				
R10	17.911	1.889	0.023	0.000
R50	27.144	3.770	23.178	1.711
R100	46.575	1.347	32.450	0.542
R150	31.445	3.836	11.017	0.196
HeS1				
R10	23.228	11.158	7.508	0.021
R50	32.631	11.378	9.413	1.181
R100	25.533	8.031	15.427	0.616
R150	21.795	9.375	9.275	−0.398
HeS2				
R10	24.122	4.354	8.363	2.485
R50	43.031	1.401	23.747	0.011
R100	90.970	4.558	49.133	1.808
R150	122.473	9.117	62.540	−0.222
Average	37.755	7.399	18.721	1.044

Note: STPM-SP = synchromodal transport planning model with shippers' preferences. SI* and CI* are the satisfaction improvement and cost increase for the solutions with maximum satisfaction improvement, respectively. SI and CI are the satisfaction improvement and cost increase for the solutions with the most cost-efficient satisfaction.

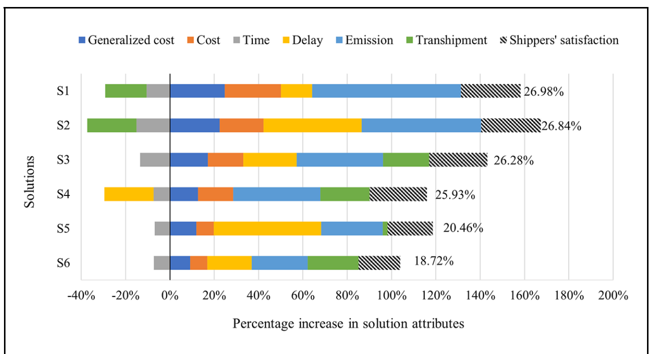

Figure 6. Comparison of the base solution and the Pareto solutions in HoS1.

72% of shippers had increased satisfaction whereas 28.1% experienced setbacks. About 66% of the shippers experienced a satisfaction increase of less than 50%, whereas 6% of shippers had a satisfaction decrease of more than 100%.

Under heterogeneous preferences, Figure 8 compares the base solution generated by STPM and the Pareto solution proposed by STPM-SP. Among the Pareto solutions, S1 demonstrated the greatest improvement in shippers' satisfaction, with an increase of around 23%, followed by S2. The main reasons for such an

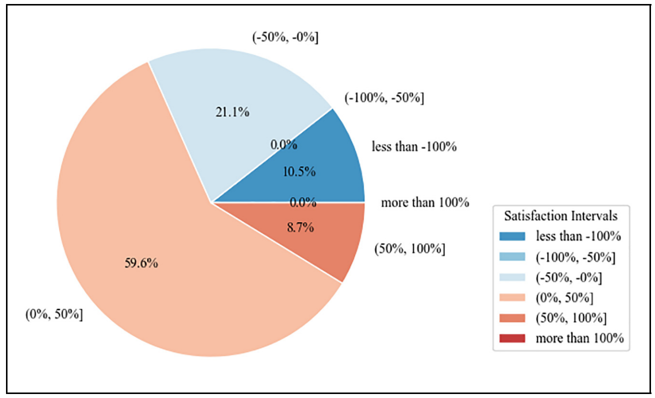

Figure 7. Proportions of shippers based on satisfaction improvement in HoS1.

improvement included the reduction in delay, transport time, and transport cost, although this came at the expense of higher emissions. Another solution, S6, also exhibited significant reductions in delay and transport costs while requiring more time and transshipment. Most Pareto solutions reduced delays, but involved a rise in emissions and transshipment. This may be the result of using higher-emission transport modes, such as trucks, which can offer shorter delivery times. More transshipment activities were observed in S1 to S5, which could facilitate the shifting of cargo from higher-disturbance routes to lower ones, thus resulting in less delay., Transshipment additionally facilitates the integration of different transport modes and routes, enabling transport plans that are better aligned with shippers' expectations for various transport attribute combinations. For instance, single-modal transport can only offer mode-specific trade-offs between time and cost, whereas transshipment allows for leveraging the characteristics of different modes. These findings also align with the assertion that transshipment can add more flexibility to the operating plans and leverage the advantages of intermodal transport (71, 72).

Figure 9 illustrates the average distribution of shippers based on their satisfaction improvement in instances with 100 requests. It was observed that the majority of shippers (68%) experienced a higher level of service, with 60% of the improvement falling within the range of 0% to 50%. Although some shippers experienced lower satisfaction, in practice, it will be crucial to investigate the underlying reasons and take measures to prevent significant decreases in satisfaction for these shippers.

Figure 10*a* shows the distribution of improvements across shipper classes. The proportions of shippers in Classes 1, 2, 3, and 4 who experienced satisfaction improvements are 67%, 76%, 80%, and 43%, respectively. For Class 4, which prioritizes cost and delay, the lowest proportion of satisfaction improvement suggests

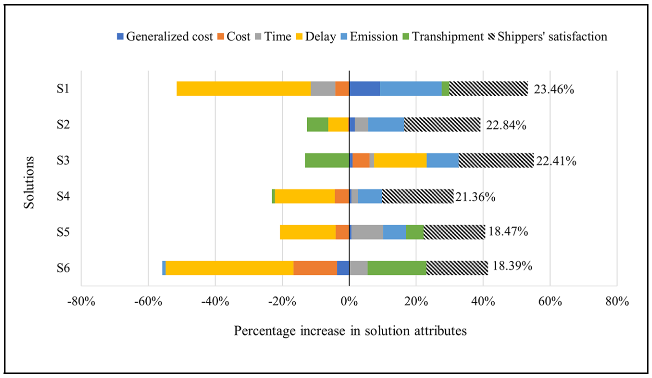

Figure 8. Comparison between the base solution and the Pareto solutions in HeS1.

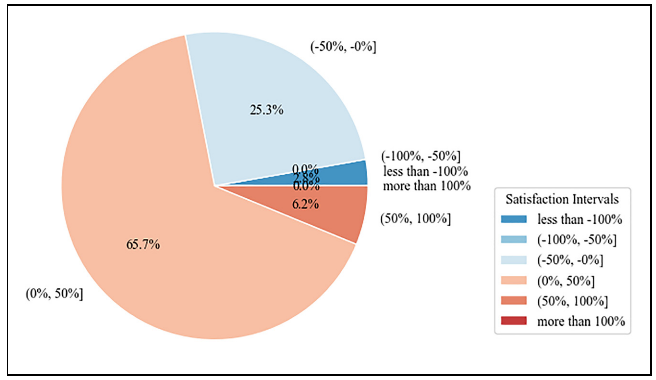

Figure 9. Proportions of shippers based on satisfaction improvement in HeS1.

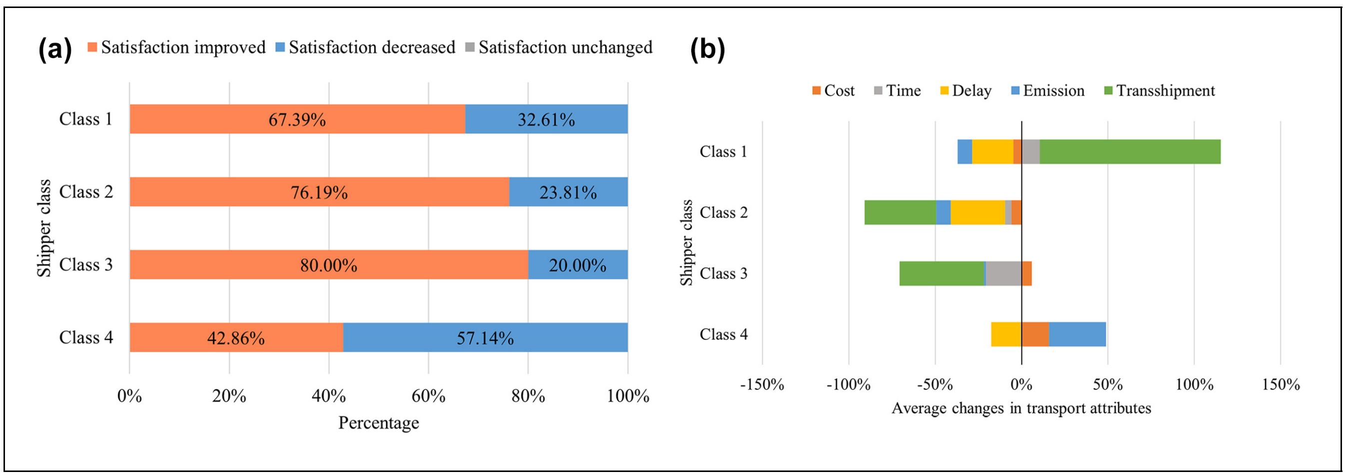

Figure 10. Planning result analysis in HeS1: (*a*) changes in satisfaction and (*b*) changes in transport attributes.

that enhancing satisfaction is more challenging. This may be attributed to the stronger trade-off between cost and delay within this class, making it more difficult to achieve significant improvements through adjustments in transport plans.

Based on Figure 10*b*, compared with the solution produced by STPM, Class 1 was provided with services involving more shifts of cargo between modes and routes for fewer disturbances. Despite the potential time increase from transshipment, the delivery for this class experienced significantly fewer delays. This outcome was consistent with the preferences of this class, which placed a greater emphasis on minimizing delays. In the case of Class 3, the eco-conscious shipper group, although the average emission reduction was only 1%, the 21% decrease in transport time was the key factor contributing to their satisfaction. This finding highlights the importance of having a comprehensive understanding of shippers' preferences rather than relying on partial knowledge. It is crucial to recognize that improvements in attributes that may not be the primary priority for shippers can still lead to increased satisfaction.

Conclusions

In this section, we conclude this work, offer insights for transportation service providers and policy makers, and discuss future research directions.

Summary

This study developed a foundational approach for integrating synchromodal transport planning and preference learning. The proposed approach could serve as the foundation for user-oriented synchromodal transport services and could be used by freight forwarders to improve the services to shippers based on preference learning. A preference learning method was proposed based on artificial NNs to capture the preference information from shippers' ranking data in transport operations. An STPM-SP was proposed to support the decision making of freight forwarders incorporating shippers' preferences. The model considered two objectives: minimizing the total cost and maximizing shippers' satisfaction. ALNS was customized to solve the STPM-SP.

The proposed preference learning method effectively captured both linear and nonlinear relationships between variables and utilities using large-scale datasets. It also identified the heterogeneity of preferences with the information from historical decisions. In comparison to statistically based discrete choice models, the artificial NN structure has the potential to simplify the preparatory work required for model specification, reducing the risk of inappropriate specifications, yet this comes at the cost of a large sample size and extra steps to ensure the interpretability of the results. The planning results demonstrated that the STPM-SP effectively found solutions with a significant satisfaction improvement of about 37%. The distribution of shippers' satisfaction indicated that achieving satisfaction improvement was not only related to the allocation of extra resources but also involved a trade-off between the resources assigned to shippers. The STPM-SP optimized this trade-off to maximize overall satisfaction.

Managerial Insights

Based on the conclusions, we can provide several managerial insights for transportation service providers and policy makers. First, a better understanding of shippers' preferences could help freight forwarders to identify gaps between the current service level and shippers' expectations. There may be scenarios where improving attributes that are not the top priority could nonetheless result in increased shipper satisfaction. Second, the integrated approach of synchromodal transport planning and preference learning could be used in synchromodal transport planning with real-time information updates. When freight forwarders are required to make prompt decisions to accommodate real-time modifications, instead of needing to consult shippers frequently, freight forwarders could leverage their knowledge of shippers' preferences to make quicker and more informed decisions. Furthermore, artificial NNs can autonomously capture nonlinear and heterogeneous relationships between variables rather than relying on strong hypotheses about model specifications. However, the potential trade-offs should also be noted, including model explanation capability, hyperparameter tuning, and the requirement for a large sample size. Last, implementation of the proposed model requires adequate data storage and management systems for the logistics sector. The systems should be capable of storing extensive data generated by shippers and transport activities, and facilitate its retrieval for preference learning. This information includes shippers' IDs, their rankings of transport plans, and the specific attributes associated with alternative plans.

Research Limitations and Future Research

In this section, we discuss the limitations of this work and offer several suggestions for future research. First, owing to data unavailability, this work used synthetic preferences and generated demand data, which may not have captured the full range of factors and complexity of real-world scenarios. It will be crucial to incorporate actual data on shipper choices and requests in future research, which will better demonstrate the applicability and effectiveness of the models. Second, the BL model is a basic form of the discrete choice model and does not fully represent the capabilities of the entire discrete choice modeling family. In future research, more advanced model structures could be explored for comparison, such as latent class (32) and mixed logit models that handle heterogeneity in different ways. Furthermore, this research showcased the shippers' satisfaction improvement by comparing the solutions of the STPM and STPM-SP, whereas a comparison between STPM-BL (or those with other logit models) and STPM-SP would provide further insights into the efficiency of the proposed models specifically based on real-data availability. Moreover, although the proposed model enhanced overall satisfaction, it may also result in an uneven distribution of satisfaction among shippers. To address this, future research might customize the objective functions and constraints. For example, minimizing the negative tail of shipper dissatisfaction and incorporating the constraints to guarantee the satisfaction of specific shippers might help achieve a more balanced and equitable distribution of satisfaction. This would better reflect real-world transport operations and improve the applicability of the optimization models. Last but not least, as the transport system serves shippers over time, the proposed model could be further developed for online learning of the system and accommodating real-time changes. This would further build the capability of freight forwarders to provide transport plans that adapt to the evolving preferences of existing shippers and align with the preferences of new shippers.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: M. He, Y. Zhang, B. Atasoy; data collection: M. He, Y. Zhang, B. Atasoy; analysis and interpretation of results: M. He, Y. Zhang, B. Atasoy; draft manuscript preparation: M. He. All authors reviewed the results and approved the final version of the manuscript.

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Supplemental Material

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