Integrated Synchromodal Transport Planning and Preference Learning

MASTER OF SCIENCE THESIS

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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. Nevertheless, limited research examined the benefit of considering shippers' preferences in the decision-making of synchromodal transport planning and the collection of relevant data is still not straightforward. This research proposes an innovative framework to learn shippers' preferences in synchromodal transport operations and optimize transport services accordingly. A preference learning method is developed to capture shippers' preferences through pairwise comparisons of transport plans. In order to model the underlying complex nonlinear relationships and detect heterogeneity in preferences, artificial neural networks are employed to approximate shippers' utility for a specific plan. Based on the learned preference information, a synchromodal transport planning model with shippers' preferences (STPM-SP) is proposed, with the objectives of minimizing the total transportation cost and maximizing shippers' satisfaction. An Adaptive Large Neighborhood Search algorithm is developed for solving this optimization problem. This algorithm takes into account the two different objective functions and searches for Pareto solutions to the planning problem. A case study is conducted based on the European Rhine-Alpine corridor to demonstrate the feasibility and effectiveness of the proposed methodological framework. Basic discrete choice models, binary logit models, are used as benchmarks for preference learning and the synchromodal transport planning model without preferences (STPM) is used as the benchmark for planning. The results show that the proposed preference learning method has better predictive power than the baseline model, achieving higher accuracy and lower variation. With the consideration of shippers' preferences, STPM-SP can significantly increase shippers' satisfaction with transport services. Scenarios with different types of preferences are tested and results show that the average of maximum improvements in satisfaction reached 37.76%. 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.

Preface

I would like to express my gratitude to the committee. I am thankful to all the committee members for their expertise, and valuable input into this project.

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Chapter 1

Introduction

The aim of this research is to propose a theoretical framework for the integration of sychromodal transport planning and shippers' preference learning. In this chapter, the motivation and the framework of this thesis are discussed. Section 1.1 introduces the background information about the sychromodal transport. Section 1.2 describe the research questions. The research contribution is presented in Section 1.3. The scope and structure of this thesis are shown in Section 1.4.

1.1 Research background

Synchromodal transport is an emerging concept in logistics that evolved from intermodal transport [2, 3, 4]. It enables the flexibility to switch between available transport modes or routes [5], and can substantially reduce transportation costs, increase transportation efficiency, and promotes emissions reductions for the transport process. As the organizer and service provider of the transport system, freight forwarders respond to shippers' requests for transport, formulate transport plans, and assign transport tasks to carriers [6]. The objectives of synchromodal transport operation commonly stem from the perspective of freight forwarders, such as minimizing total transport cost [1, 7], total transport time [8], resource use [8], and CO_2 emissions [9]. As the customers of the transport system, shippers play a key role in the real-world operation of transport systems. 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 [10]. However, only a few researchers investigated the incorporation of shippers' preferences into the synchromodal transport operation [11, 12].

There are still challenges regarding the acquisition and modeling of shippers' preferences. The traditional methods for studying shippers' preferences are commonly based on 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 biases and challenges associated with large-scale 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 simultaneously assess various attributes of transport services and precisely describe to what extent they value a specific attribute. In addition, discrete choice models have been used to explore shippers' attitudes and behaviors [13, 14, 15]. As a statistical-based method, discrete choice models require prior knowledge of utility to predefine the relationships between variables. The capacity of models can be restricted if the real preferences are not aligned with the model settings. With the advance of data collection techniques, it is important to investigate the preference learning methods that can leverage large datasets and automatically capture the complex relationships directly from data.

To this end, this thesis develops a foundational framework for integrating synchromodal transport planning and preference learning to capture shippers' preferences in the transport process and enable freight forwarders to make more informed decisions. This framework can serve as the foundation for the user-oriented synchromodal transport services that freight forwarders provide services while simultaneously learning from shippers' preferences. It emphasizes the data collection within the transport system and improves services based on the preferences of shippers. A preference learning model is proposed to estimate shippers' preferences from their actual decisions on transport services. Based on the artificial neural network architecture, the proposed preference learning method is capable of modeling non-linear relationships within the decision-making process, as well as distinguishing heterogeneity among different shipper classes. Rather than relying on hypothetical responses, the preference information is derived from actual choices made by shippers on their transport plans. A synchromodal transport planning model considering shippers' preferences is established to propose transport solutions, solved by This research develops a synchromodal transport planning model with shippers' preferences (STPM-SP), with two objectives of minimizing the total cost and maximizing the shippers' satisfaction. The model is solved using a modified heuristic algorithm based on the Adaptive Large Neighborhood Search (ALNS) proposed by Zhang et al. (Z2022synchromodal). By combining preference learning and synchromodal transport planning, shippers' preferences can be identified during the process of transport operations and used to inform the next round of transport planning. 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.

1.2 Research questions

The main research question of this thesis is how to learn shippers' preferences in the process of transport operation and provide better transport services accordingly. To address the main research question, specific research sub-questions (RQ) are presented as follows:

RQ 1: How to learn shippers' preferences from their rankings on alternatives of transport plans?

Considering shippers' rankings on transport plans collected during the transportation, the task is to learn shippers' preferences and find out how shippers evaluate the transport plans. Section 2.2 introduces how shippers' choices on transport plans are collected and how the data can be used in preference learning. A preference learning method based on artificial neural networks is developed to capture shippers' preferences and predict shippers' satisfaction with new transport plans.

RQ 2: To what extent the true preferences can be captured from the ranking data?

Using the preference learning method to capture underlying preferences, the task is to evaluate the prediction capacity and explanation ability of the preference learning method. The true preference and the learned preference will be compared to understand to what extent the information is captured by the proposed model. The performance of the proposed learning model will be evaluated together with the baseline model using the criteria introduced in Section 3.3.

RQ 3: How to incorporate preferences into synchromodal transport planning?

Section 2.4 discusses the importance of incorporating shippers' preferences into synchromodal transport planning. With shippers' preference information, the research problem is to propose transport solutions to respond to shipping requests respecting the constraints with the objectives to minimize the cost and maximize shippers' satisfaction. A synchromodal transport planning model with shippers' preferences is developed in Section 3.2

RQ 4: To what extent the transport services can be improved according to the learned preferences?

Considering the same set of requests and transport resources, the question is how the (near) optimal solutions, proposed by the traditional transport planning model and preference-based transport planning model, could be different in terms of transport cost and user satisfaction. To address the research question, the transport services proposed by the synchromodal transport planning model with and without shippers' preferences will be comparatively analyzed.

1.3 Research contribution

This thesis presents a methodology for the integration of synchromodal transport planning and shippers' preference learning, which can capture shippers' preferences in the transport process and optimize the transport services accordingly. The optimization model for synchromodal transport planning problem is based on the planning model proposed by Zhang et al. [4]. This research contributes to the literature in the following aspects:

Contribution 1: proposing a fundamental framework for the integration of synchromodal transport planning and shippers' preference learning.

The research on synchromodal transport operation has broadly considered the benefits and interests of freight forwarders (i.e. freight forwarders and carriers) [1, 16]. This research explores the potential improvement of transport services by incorporating the shippers' preferences. A limited number of studies have utilized preference information in the synchromodal planning process. In comparison to the work of Shao et al., Zhang et al.[11, 12], this research focuses on the integration of the learning process and the planning process, utilizing the shippers' preference information (revealed preferences) generated in transport operations to inform the decision-making of freight forwarders.

Contribution 2: proposing a data-driven learning method to capture shippers' preferences and comparatively exploring the abilities of the statistical-based method and the data-driven method in preference learning.

This research designs a process to collect shippers' feedback, which can be used to capture shippers' preferences in their actual decision-making process, resulting in a more accurate preference reflection compared to the traditional hypothetical survey. This research also examines the statistical-based and data-driven preference learning model performance with different sample sizes, and variable relationships, and gains insights into the reasons for their respective performance.

1.4 Thesis overview

As shown in Figure 1.1, this research proposes a fundamental framework for synchromodal transport planning with shippers' preference learning, enabling the freight forwarder to assign services to shippers and learn shippers' preferences simultaneously. The synchomodal transport planning method and the preference learning method are combined to improve the transportation process. Sychomodal transport planning solves the transport planning problem considering requests, vehicles, terminals, and time schedules. For each request, the shipper will rank alternative transport plans based on their actual preferences, which is used as feedback for preference learning and transport planning. The learned preferences will be incorporated into the planning process to enhance the level of service and increase shipper satisfaction.

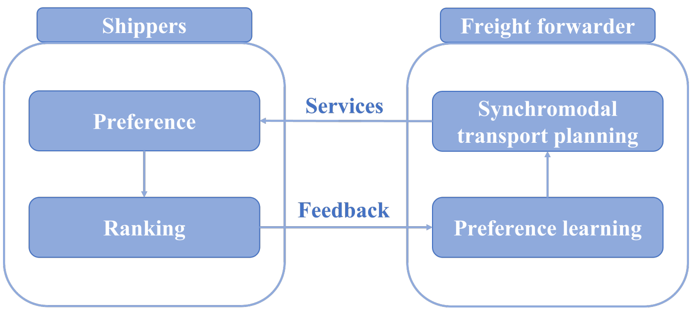


Figure 1.1: Thesis overview

1.4.1 Thesis scope

The thesis considers operational-level synchromodal transport planning. In the real transport system, there are mainly three stakeholders, a freight forwarder, shippers, and carriers. The freight forwarder is the operator and the controller of the transport system who collects requests from shippers and assigns the resources of carriers and routes to these requests. Shippers are considered to be the customers, and the freight forwarder and carriers are considered to be the service provider of the system. As the service provider, the roles of carriers and freight forwarders can be interconnected, therefore, this research specifically focuses on the interaction between freight forwarders and shippers.

The strategic layout is assumed to be set in advance. Specifically, the existing transport network, the connections between terminals, the capacity of transportation vehicles, and transportation infrastructure are considered static, which are modeled as constraints in the transport planning problem. In reality, strategic planning may change due to market conditions, customer needs, and emerging technologies. The adjustments and modifications of the transport network and transport infrastructure are not considered in this research.

The transport network used in this research is the European Gateway Services (EGS) network of Rhine-Alpine corridor [1]. Terminals included ports or hubs for transport operations, which contain the transfer terminals and the origins and destinations of requests. As for transport vehicles, trucks, trains, and barges are considered. The capacity of each vehicle and the number of each mode are modeled as limited resources.

The way to collect preference data is to inquire about shippers and collect their ranking results on transport plans while they interact with a real transport operating system. In this research, shipper choices are generated based on predefined utility functions, which specify the value that a simulated shipper assigns to different transport plans. The reasons for utilizing synthetic preference data, detailed utility calculations, and decision rules are discussed in Section 3.3.2.

1.4.2 Thesis structure

The thesis follows the structure as listed below:

- Chapter 2 shows the literature review summarizing the research highlights in relevant fields, including methodology innovation in choice analysis, shippers' preference modeling, and synchromodal transport planning;
- Chapter 3 states the research problems and introduces the proposed methodology for synchromodal transport planning with shippers' preference learning;
- Chapter 4 presents the evaluation results of preference learning and synchromodal planning with shippers' preferences. To evaluate the predictive performance, the learning results of the proposed preference learning are compared with the results of discrete choice models. Different scenarios are conducted to investigate the benefits of incorporating shippers' preferences into synchromodal transport planning.
- Chapter 5 discusses the research methodology and results.
- Chapter 6 summarizes the findings of this thesis and its limitations.

Chapter 2

Literature Review

This chapter presents the review methodology and the literature review covering three research domains: shippers' preference analysis, machine learning in transport choice analysis and intermodal transport planning.

2.1 Review methodology

The review methodology aims to facilitate an efficient, in-depth, comprehensive literature review related to the field of synchromodal transport planning and shipper preference learning, and determine how this research can contribute to the current literature. Based on the research objective, the literature review is structured into three domains: shippers' preferences, machine learning in transport choice analysis, and intermodal transport planning. The survey follows a three-step process, which includes literature searching, literature evaluation, and literature review.

During the literature searching, this survey uses two databases, Web of Science and Scopus. The initial search is conducted using the most relevant keywords, 'shippers' preferences', 'machine learning in choice analysis', and 'intermodal transport planning'. The focus is to first locate review articles to have a 'roadmap' of previous research and identify influential works in the field. Then, the keywords are expanded to include more specific terms, for example, 'discrete choice model', 'artificial neural networks', 'synchromodal transport'. The expanded set of keywords is used for more comprehensive literature searching, with an emphasis on newly published works to ensure up-to-date information is included.

The second step is the evaluation of the literature with the main task to categorize it into three categories, highly relevant, relevant, and less relevant for each topic. A significant advantage of starting from searching review articles is that with the roadmap of existing literature, we can be more aware of the relevance and influence of searched literature. These categorizations then guide the literature review process, with greater attention given to the highly relevant articles.

Based on the research roadmap and classification, we can develop an initial framework of the review, with ideas on the aspects to be analyzed and the key focus of the discussion. For each part of the research domain, the review of literature starts from the most relevant work. We will first examine the abstracts of selected articles to gain insights into their contributions and key highlights. Then, a thorough analysis is conducted including reviewing the methodology and the main findings. It is crucial to understand both the contributions and limitations of the reviewed studies to establish their connection to this research. During the literature review progress, additional relevant literature may be identified and included to ensure a comprehensive analysis of the research topic.

Following the aforementioned steps, this survey reviews a range of research works published from 1973 to 2023, including journal papers, conference articles, and books. The journals that have the highest relevance to this research are: Transportation Research Part E, Transportation Research Part C, and Transportation Research Part D. The reviewed literature 109 studies in total, with 33 studies focusing on shippers' preferences, 42 studies on machine learning in choice analysis, and 34 studies on intermodal transport planning.

2.2 Shippers' preference analysis

Extensive investigations have been conducted to identify the important service attributes in the shipper decision process. In general, transport cost, transport time, and reliability are considered to be the three core factors influencing the transport decisions of shippers [17, 18]. Transport cost is listed as the major critical factor in several research [19, 20]. The evidence is consistent regarding the negative sign of the cost attribute, which means that higher cost tends to reduce the competitiveness of transport services [21]. In addition, transit time can be a statistically significant component of transport projects [22]. For example, Kurtulus et al. [23] found that reducing transit time by 50% could increase the share of rail from 10.6% to 29.7% considering short-distance inland transport in Turkey. Kim et al. [19] indicated that shippers who offer fast delivery products would concern more about transportation time for mode choice. The value of time (VOT), has also been estimated to investigate the monetary value of unit transport time [20, 24, 25]. Reliability is commonly defined as the percentage of on-time delivery of freight/goods at the destination [21, 26, 27, 22]. Transport services with higher reliability appear to result in higher service quality and higher customer satisfaction [23]. Larranaga et al. indicated that with an increase of 1% unit on-time deliveries, rail and waterway alternatives would each gain 1.91% and 3.45% market share, moreover, the attribute reliability can sometimes be a more decisive factor than cost reductions [24]. Some other service attributes have been investigated as well, such as frequency [19, 22], flexibility [26], and risk of damage [10]. A few researchers looked into the impact of gas emissions [28, 29] and transshipment [30, 31, 32, 31], revealing the potential role of transshipment from the perspective of shippers. Nugroho et al. [33] found that companies with higher export volumes tend to be more aware of the impact of greenhouse gases on the environment. In the research of Tavasszy et al. [28], it was indicated that as environmental awareness continues to increase, shippers would be more concerned about emissions during the transportation process, despite emissions showing less significance in comparison to other criteria at that stage. Some research on transshipment showed that this option may increase cost-effectiveness by enhancing multimodal transportation and optimizing route and time scheduling [32], while on the other hand, it may also increase the risk of delays and damage to cargo [34].

All the aforementioned research used discrete choice models to explain choice behavior and investigate the impacts of potential factors, as shown in Table 2.1. The multinomial logit (MNL) model is the classic technique for choice modeling, which was first introduced by McFadden [35]. Recent research on intermodal transport choice modeling attempted to release the predetermined structures and linear characteristics of underlying functions in MNL. The exploration has leveraged the advantages of mixed logit model (MMNL), nested logit model (NL), weighted logit model (WL), conditional logit model (CL), and latent class logit model (LCMNL). For example, Nicolet et al. [36] combined MMNL and WL to investigate the mode split in freight transportation using aggregated origin-destination data. The preference variation within the population was modeled by MMNL with individual preferences to be randomly distributed within a certain range.

MNL-based models require functional form specification to capture the non-linearity relation in complex decision-making behavior [37]. Jourquin [38] argued that incorporating non-linearity in choice modeling provides more degrees of freedom for model estimation. They incorporated Box-Cox transformations (BCT) in the conditional logit model. The results showed that BCT could efficiently help overcome multicollinearity and improve the log-likelihood [38]. Jensen et al. [39] suggested that linear cost functions unrealistically restrict elasticities to the scale of the variable. The research examined the marginally decreasing sensitivity for cost in the freight model and demonstrated the necessity to take non-linearity into account [39].

Table 2.1: Comparison between the proposed model and the models in the existing literature.

Research	Influential factors	Model	Specification
Nugroho et al.(2016) [33]	cost,time,reliability,emissions,etc	mixed logit	linear
Kim et al.(2017) [19]	cost,time,reliability, frequency,etc	latent class logit	linear
Khakdaman et al.(2020) [26]	cost,time,reliability, flexibility, etc	multinomial logit model	linear
Kurtuluş et al.(2020) [23]	cost,time,reliability,frequency,etc	mixed logit	linear
Firdausiyah et al.(2021) [40]	cost,time	binary logit	linear
Nicolet et al.(2022) [36]	cost,accessibility	weighted mixed logit	linear
Román et al.(2016) [37]	cost,time,reliability,frequency	latent class logit	nonlinear
Jensen (2019)[39]	cost,time,etc	nested logit	nonlinear
Jourquin et al. (2022)[38]	cost,time,distance	conditional logit	nonlinear
Feo-Valero et al.(2022) [21]	cost,reliability,frequency,etc	mixed logit	nonlinear
This study (2023)	cost,time,delay,emission,transshipment	preference learning	model-free

2.3 Machine learning in transport choice analysis

Discrete choice models have been extensively utilized in transport behavior modeling and recognized as a powerful tool for analyzing decision-making processes [41]. However, the model structure relies on the assumptions for model specification, which could lead to oversimplification of actual decision-making processes [42], failure to capture the underlying structure of the data [43], and incorrect parameter estimation and prediction [44, 45, 42]. For instance, Torres et al. [45] examined the misspecification effects in utility functions showing when the true utility function is nonlinear, assuming a linear utility specification resulted in up to 63% relative bias.

With the growing availability of data, utilizing data-driven approaches has emerged as a promising alternative for choice analysis. Data-driven approaches can identify behavioral patterns directly from the data [46]. Compared to the statistical-based model, these approaches rely less on detailed model specifications based on prior behavior knowledge. In the context of transport choice modeling, various machine learning methods were investigated and demonstrated, including artificial neural networks (NN), random forests (RF) [47, 48, 42], support vector machine (SVM) [49, 50, 51], gradient boost model (GBM) [52, 53, 54] restricted boltzmann machines (RBM) [55] and Association Rules (AR) [46].

Among machine learning methods, artificial neural networks emerged as the workhorse model and became the most studied machine learning type in recent research [56]. When compared to discrete choice models, NNs and NN-based models exhibit superior predictive power and accuracy [57, 43, 58]. This can be attributed to their ability to automatically learn the true utility specifications [59], and uncover complex nonlinearities and unobserved information in the data [56, 60]. Sifringer et al. [43] proposed hybrid learning-based logit models in which the systematic utility consists of an interpretable part and a non-linear part derived from neural networks. The representation learning architecture enhanced MNL and NL models for utility specification. They suggested that the proposed model can achieve better predictive performance and accuracy in parameter estimation, while MNLs that ignore these non-linearities suffer a severe underfitting problem. Wang et al. [59] proposed a deep neural network architecture with alternative-specific utility functions. The results showed that the proposed model appeared to have a lower loss value in predicting the choice of trip purposes, outperforming discrete choice models including binary logit, binary mixed logit, multinomial logit, and multinomial mixed logit models. Lee et al. [58] compared the predictive capability of artificial neural networks with MNL models based on a survey dataset with 4,764 observations. The cross-validation results show that NN models outperform MNL models, with prediction accuracies around 80% compared with 70% for MNL.

Some researchers demonstrated the time efficiency of ANN in handling large volumes of data and complex model specifications [56, 57, 61]. Wong et al. [57] proposed a ResLogit model with a residual component to capture unobserved taste heterogeneity in the choice process. In contrast to baseline MNL models, the proposed models had smaller standard errors and higher efficiency in parameter optimization. Hillel [61] found that due to utilizing the gradient descent algorithm in optimum searching, the feed-forward neural network can be trained up to 200 times faster than nested logit models, moreover, the training time is significantly shorter than other machine learning methods including random forest, extremely randomized tree, and extremely randomized tree. Apart from the flexibility in model specification and efficiency in parameter optimization, another potential of ANN is its adaptivity to large and continuous streams of data, unleashing the dynamics of the decision-making process [56]. Wang et al. [59] examined the performance of NN and discrete choice models with sample size variation and indicated that the advantage of using deep neural networks would be amplified when the sample size is large. Current literature has demonstrated the benefits of NN in the transport choice modeling field [56], and more investigations and discussions remain to be conducted. Few researchers explore the efficiency of NN in learning the underlying heterogeneity in choices.

2.4 Intermodal transport planning

The intermodal transport planning problem has been broadly formulated as a single-objective optimization problem. Travel cost is considered to be the primary objective of transport operators, which is commonly composed of transport cost, loading/unloading cost, and storage/inventory cost [62]. Some researchers included additional cost in the configuration of the total cost, including delay penalties [4], emissions-related costs [63] and nonfulfilment penalties [16]. With the awareness improvement on sustainable development, the objective of minimizing carbon dioxide emissions became more frequently modeled in intermodal transport planning reseach [64, 65]. The activity-based method was widely used to calculate the carbon dioxide emissions in the transportation process, which was based on vehicle type, distance, and amount of containers [66, 1, 12, 65].

As transport objectives can be conflicted with each other in the complicated decision-making process of transport planning [67], multi-objective optimization has been used to model trade-offs between different objectives [68, 69, 63]. Zhang et al. [67] considered three objectives of the total cost, delivery time, and reliability, and combined the ϵ-constraint method and the memetic algorithm for optimum searching. Baykasoğlu and Subulan [65] explored transport solutions that compromise transport costs, transit times, and carbon emissions and compared the optimization results under crisp and fuzzy decision-making environments using multiple objective optimization approaches. Zhang et al. [9] set the first objective to maximize the number of served requests, and the second to minimize the carrier's overall cost considering operation cost, carbon tax, and delay penalty.

However, all these objectives represent the benefits of system operators. The interests of shippers and operators can be different, hence, the transport planning results from the perspective of operators may not be optimal for shippers [11]. Several research indicated that operators are more cost-sensitive than shippers [70, 21]. In the study of Feo-Valero et al. [21], it was found that the role of carriers and shippers significantly affects the impact of transport cost on port choice decisions. The reason could be that transport operators generally work with a profit margin on the price to maintain the turnover and acquire new clients [21]. Besides, the difference in the VOT was investigated [71, 25]. Shippers tend to have a higher gross VOT [25] and be willing to pay more for reliability improvement [72].

Only a few researchers considered shippers' preferences in the operation process. Shao et al. [11] used a dominance-based rough set approach to derive decision rules and require shippers to select the most important one. The selected rule was then presented as a new constraint for the optimization problem. While the process of operators consistently seeking input from shippers during each planning phase can be time-consuming. Similarly, shippers may encounter difficulties in effectively evaluating and comparing multiple transport attributes simultaneously. Zhang et al. [12] applied fuzzy set theory and obtained preference information through shippers' vague expressions on the importance of attributes including cost, time, reliability, risk, and emissions. Preferences of shippers were set as constraints that ensured the calculated satisfaction was higher or equal to the predefined benchmark. The potential problem could be 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.

2.5 Research gap

A comprehensive understanding of shippers' preferences can empower transport freight forwarders to provide user-oriented targeted transport services and strengthen long-term business relationships. In synchromodal transport research field, many studies addressed the transport planning problem from the perspective of freight forwarders. It is unclear how to capture the preference information from shippers' feedback data in the transport operations, as well as how this information can inform freight forwarders in decision-making. There is a lack of a fundamental framework that integrates synchromodal transport planning and shipper preference learning.

Shippers' preferences have been explored in their choices of transport modes [73, 27, 19, 17], terminals [30, 21, 33], and service providers [10]. While different from other logistic transport systems, transport solutions can involve multiple transport modes, terminals and carriers in the synchromodal transport system. Hence shippers' satisfaction with the transport plans can be more straightforward to reflect their preferences rather than satisfaction with specific transport modes or carriers. Many studies applied discrete choice models to investigate shippers' preferences as shown in Table 2.1. However, discrete choice models rely on prior knowledge of shippers' preferences and require model specification for utility estimation. Previous studies have demonstrated that these assumptions can restrict the model capacity, and incorrect specified model could mislead the estimation results [56]. In addition, when collecting shipper preference information from survey data, there can be inaccurate expressions and hypothetical biases.

Artificial neural networks have great potential in the field of transport behavior modeling, showcasing the ability to handle large-scale datasets of revealed preferences [56]. There is a need to comparatively explore the abilities of this emerging technology and the classic method (i.e. discrete choice models) with respect to prediction and explanation. Furthermore, in shippers' preferences analysis, some studies applied latent class models to reveal underlying preference heterogeneity [19, 37], while few research investigates whether artificial neural networks can distinguish the heterogeneity directly from the dataset.

The research on synchromodal transport operation has broadly considered the benefits and interests of system operators (i.e. freight forwarders and carriers) [1, 16]. Although many researchers have demonstrated the significance of incorporating the shippers' benefits into operations [10], only a limited number of studies have utilized preference information in the synchromodal planning process [12, 11]. In comparison to the work of Zhang et al.[12] and Shao et al. [11], this study focuses on the integration aspect that utilizes the shippers' preference information generated in the transport operations to inform the decision-making of freight forwarders.

To this end, this research proposes a theoretical framework for the integration of synchromodal transport planning and shipper preference learning. This framework can serve as the foundation for the user-oriented synchromodal transport services that freight forwarders provide services while simultaneously learning from shippers' preferences. It emphasizes the data collection within the transport system and improves services based on shippers' preferences. A preference learning method is developed to capture shippers' preferences from their ranking on transport plans. Artificial neural networks are used to approximate shippers' satisfaction with transport services. The derived preference information is incorporated into the synchromodal transport planning process to generate solutions considering the benefits of both shippers and freight forwarders.

Chapter 3

Methodology

3.1 Problem statement

As shown in Figure 3.1, this research proposes a fundamental framework for the integration of synchromodal transport planning and shipper preference learning. The proposed framework aims to address two major research problems: the bi-objective synchromodal transport planning problem and the shippers' preference learning problem. The synchromodal transport planning problem focuses on finding Pareto solutions that optimize both cost and satisfaction using the transport resources and captured shippers' preferences. This is a challenging problem due to the integration of shippers' preferences into the planning process and the potential conflicts between cost and satisfaction. The planning model should be able to autonomously predict the corresponding satisfaction and balance the two objectives and model the trade-offs. The aim of shippers' preference learning is to capture unknown preferences based on shippers' ranking data on alternative transport plans. The challenges lie in the capacity to learn complex relationships between different attributes and the fact that shippers' preferences can be heterogeneous.

To address these challenges, this research proposed a mathematical planning model with preference learning for synchromodal transport decision-making. The preference learning model employs artificial neural networks to estimate the utility function, which is then used to calculate shippers' satisfaction. The bi-objective planning model allows freight forwarders to propose transport solutions with high service quality, resulting in win-win outcomes for both freight forwarders and shippers. Notations used in models are shown in Table 3.1.

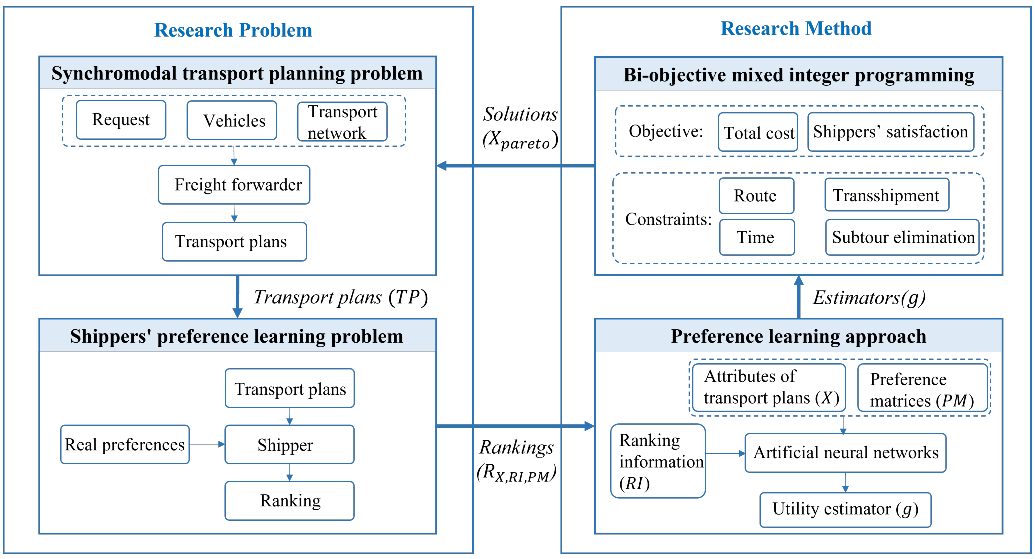


Figure 3.1: Research framework

Table 3.1: Notations in the synchromodal transport planning model

Symbol	Description
Sets	
R	Set of requests indexed by r
S	Set of shippers indexed by s
K	Set of vehicles indexed by k
K_r	Set of vehicles served request r
K_b	Set of barges
K_t	Set of trains
N	Set of terminals
T	Set of transshipment terminals
Parameters	
c_k^t	Transport cost per kilometer per container using vehicle k. unit: euro
c_k^l	The loading (or unloading) cost per container using vehicle k. unit: euro
c_k^s	The storage cost per container per hour using vehicle k. unit: euro
c_k^w	The cost of waiting time per vehicle per hour using vehicle k. unit: euro
c_k^e	The cost of emission tax per container per distance using vehicle k. unit: euro
c_r^d	The delay penalty per container per hour for request r. unit: euro
d_{ij}	Distance between terminal i and j. 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
e_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
$[a_{p(r)}, b_{p(r)}]$	Pick-up 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
Variables	
x_{ij}^k	Binary variable; 1 if vehicle k uses the route between terminal i and j.
$y_{ij}^{k,r}$	Binary variable; 1 if request r transported by vehicle k uses the route between terminal i and j.
z_{ij}^k	Binary variable; 1 if terminal i precedes terminal j in the route of vehicle k.
$s_{i,r}^{k,l}$	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: hour
$t_{r,i}^{arr,k}$	The arrival time of request r served by vehicle k at terminal i. unit: hour
$t_{r,i}^{ss,k}$	Service start time of request r served by vehicle k at terminal i. unit: hour
$t_{r,i}^{se,k}$	Service finish time of request r served by vehicle k at terminal i. unit: hour
$t_i^{arr,k}$	The arrival time of vehicle k at terminal i. unit: hour
$t_i^{dep,k}$	The departure time of vehicle k at terminal i. unit: hour
$t_i^{wait,k}$	The waiting time of vehicle k at terminal i. unit: hour

3.1.1 Synchromodal transport planning problem

This research considers a transport system with two types of stakeholders, 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. Specifically, a *request* $r \in R$ is to transport containers from the origins to the destinations, meeting the requirement of shippers. The information of a request includes the pickup terminal p_r, the delivery terminal d_r, pick-up time window $[a_{p(r)}, b_{p(r)}]$, delivery time window $[a_{d(r)}, b_{d(r)}]$, and the number of containers q_r. We use semi-hard time windows where containers must be picked up during the corresponding time windows. Delivery delays occur when the delivery time exceeds the time limit $b_{d(r)}$. A *transport plan* $tp_r \in TP$ is the service that the freight forwarder provides to the shipper according to the request r. A transport plan includes information on the route l_r and vehicle(s) k_r to service the request r with time schedule. A transport plan can be characterized by attributes including transport cost c_r, transport time t_r, emission e_r, delay d_r, and transshipment $trans_r$. The transport network includes terminals and available corridors. Transport vehicles include trucks, trains, and barges. The number of barges and trains is fixed, while the number of trucks is not limited. The capacity of each vehicle is modeled as a limited resource. The loading unit refers to a standardized container measured in Twenty-foot Equivalent Units (TEU).

3.1.2 Shippers' preference learning problem

The aim of shippers' preference learning is to find out how transport choices are made by shippers. Knowing the customer allows the freight forwarder to understand the shippers' considerations and provide better service accordingly [12]. In this research, the prior information about the shippers' preferences is the features of transport plans they may be interested in. Based on previous research on shippers' behavior, it is assumed that shippers would evaluate the transport plans based on five criteria: transport cost c_r, transport time t_r, emission e_r, delay d_r, and transshipment $trans_r$. For each request, shippers are queried to rank several alternative plans provided by the freight forwarder. The ranking results are then collected and used as the supervision of preference learning. Compared to the query regarding a specific feature, such as asking shippers to rate each attribute on a predetermined scale of importance, this ranking method can be more accurate to reflect actual preferences. This is because the ranking result is obtained in the shippers' real decision-making process, that is, shippers will be more benefitted if the freight forwarder assigns them the higher-ranking alternative. It is noted that the purpose of collecting rankings is for preference learning rather than direct implementation, thus, the freight forwarder does not necessarily implement the top-ranked plan to operate the system. The final decision is made by the freight forwarder as a central controller of the transport system aiming for system optimality.

3.2 Synchromodal transport planning

This section introduces the mathematical model for synchromodal transport planning. The objectives and constraints are formulated, and the solution algorithm is designed for freight forwarders to propose transport plans for shippers.

3.2.1 Mathematical model

The synchromodal transport planning model with shippers' preferences (STPM-SP) has two objectives, minimizing the total cost and maximizing the shippers' satisfaction. The synchromodal transport planning model without shippers' preferences (STPM) is used as a benchmark, which is a single-objective optimization model. STPM is used when the freight forward has no information on shippers' preferences, the modeling goal is to propose optimal transport plans from the perspective of the freight forwarders [4]. This research first uses STPM to propose initial alternatives for shippers and then explores shippers' preferences using preference learning. When the learned preference is reliable, it is incorporated into STPM. Then, STPM-SP will use the learned preference and consider the benefits of both carriers and shippers.

Sychromodal transport planning without shippers' preferences

When the freight forwarder has no information on shippers' preferences, the goal of the synchromodal transport planning problem is to propose optimal transport plans from the perspective of freight forwarders. The objective is to minimize total transport cost (Z_c), which 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}). The transit cost is the cost related to vehicle usage, positively associated with travel distance and loads of requests. Transfer cost is the sum of terminal transfer cost and pick-up/drop-off transfer cost. Storage cost includes the storage time at terminals and pickup depots. The emissions calculation follows an activity-based approach introduced by Demir et al. [63], which considers factors such as vehicle type, distance traveled, and the number of containers. The delay penalty is associated with the load and the delay time. The objective of minimizing the total cost (Z_c):

$$\min\ Z_c = C_{transit} + C_{transfer} + C_{storage} + C_{emission} + C_{waiting} + C_{delay} \tag{3.1}$$

$$C_{transit} = \sum_{k\in K}\sum_{r\in R}\sum_{i,j\in N} c^t_k q_r d^k_{i,j} x^k_{ij} \tag{3.2}$$

$$C_{transfer} = \sum_{k,l\in K}\sum_{r\in R}\sum_{i\in N}(c^l_k + c^l_l) q_r s^{kl}_{i,r} + \sum_{k\in K}\sum_{r\in R}\sum_{i\in N} c^l_k q_r (y^{k,r}_{p_r i} + y^{k,r}_{id_r}) \tag{3.3}$$

$$C_{storage} = \sum_{k,l\in K}\sum_{r\in R}\sum_{i\in N} c^s_k q_r s^{kl}_{i,r}(t^{ss}_{l,r,i} - t^{se}_{k,r,i}) + \sum_{k\in k}\sum_{r\in R}\sum_{i\in N} c^s_k q_r y^{k,r}_{p_r i}(t^{ss}_{k,r,p_r} - a_p(r)) \tag{3.4}$$

$$C_{emission} = \sum_{k\in k}\sum_{r\in R}\sum_{i\in N} c^e_k e_k q_r d^k_{i,j} y^{k,r}_{i,j} \tag{3.5}$$

$$C_{waiting} = \sum_{k\in K_b\cup K_t}\sum_{i\in N} c^w_k t^{wait,k}_i \tag{3.6}$$

$$C_{delay} = \sum_{r\in R} c^d_r q_r t^d_r \tag{3.7}$$

Synchromodal transport planning with shippers' preferences

Previous research has shown statistically significant differences between the preferences of operators and shippers when it comes to decision-making in transport services [10, 21]. With the aim of long-term business relationships between carriers and shippers, this research solves the synchromodal transport planning problem using two objectives: minimizing the total cost (Z_c) and maximizing the shippers' satisfaction (Z_s).

The total transport cost (Z_c) is calculated in the same way in the classic STPM as shown in Eq(3.1). In Eq (3.8), the total shippers' satisfaction (Z_s) is the sum of the satisfaction of each shipper with respect to the transport plans assigned to them. The relations between shippers' preferences and transport plans ($g(x, \theta)$) will be explored using preference learning, as introduced in Section 3.3

$$\min\ Z_s = -\sum_{r\in R} g(x_r, \theta_r) \tag{3.8}$$

Based on the assumption on shippers' preferences (in Section 3.1.2), a transport plan 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 determined by Eq.(3.9-3.13). Transshipment refers to the number of transshipment for the containers of request r during the transport operation. The parameter tr_s is used to scale the variable tr_r. Its purpose is to adjust the scale of tr_r so that it is comparable to other attributes in the analysis.

$$c_r = \frac{c_{transit,r} + c_{transfer,r} + c_{storage,r}}{dis_r * l_r} \tag{3.9}$$

$$t_r = \frac{\sum_{k \in K_r} (t^{se,k}_{r,d_r} - t^{ss,k}_{r,p_r})}{dis_r} \tag{3.10}$$

$$dt_r = \frac{\max(0, t^{se}_{d_r,r} - b_{d(r)})}{\sum_{k \in K_r} (b_{d(r)} - a_{p(r)})} \tag{3.11}$$

$$e_r = \frac{\sum_{k \in K_r} \sum_{(i,j) \in N} e_k y^{k,r}_{i,j} q_r d_{i,j}}{dis_r * l_r} \tag{3.12}$$

$$tr_r = \sum_{(k,l) \in K_r} \sum_{i \in T} \frac{s^{k,l}_{i,r} q_r}{tr_s} \tag{3.13}$$

Constraints of synchromodal transport planning

Constraints (3.14–3.18) are the routing constraints. Constraints (3.14) and (3.15) ensure that vehicles and requests start/end at designated starting/ending depots or pickup/dropoff locations. Constraints (3.16–3.18) ensure the flow conservation for both vehicles and containers. Constraints (3.19) are the capacity constraints. Constraint (3.20) indicates that vehicle k is marked as 'used' when there is at least one request transported by vehicle k between terminal i and terminal j.

$$\sum_{j \in N} x^k_{s_k,j} = \sum_{j \in N} x^k_{j,e_k} \leq 1 \quad \forall k \in K_b \cup K_t \tag{3.14}$$

$$\sum_{k \in K} \sum_{j \in N} y^{k,r}_{p_r,j} = \sum_{k \in K} \sum_{j \in N} y^{k,r}_{j,d_r} \leq 1 \quad \forall k \in K, r \in R \tag{3.15}$$

$$\sum_{j \in N} x^k_{i,j} = \sum_{j \in N} x^k_{j,i} \quad \forall k \in K_b \cup K_t, i \in (N \setminus (s_k \cup e_k)) \tag{3.16}$$

$$\sum_{j \in N} y^{k,r}_{i,j} = \sum_{j \in N} y^{k,r}_{j,i} \quad \forall k \in K, r \in R, i \in (N \setminus (T \cup s_k \cup e_k)) \tag{3.17}$$

$$\sum_{k \in K} \sum_{j \in N} y^{k,r}_{i,j} = \sum_{k \in K} \sum_{j \in N} y^{k,r}_{j,i} \quad \forall r \in R, i \in T \tag{3.18}$$

$$\sum_{r \in R} q_r y^{kr}_{ij} \leq u_k x^k_{ij} \quad \forall k \in K, \forall i \in N \tag{3.19}$$

$$y^{k,r}_{i,j} \leq x^k_{i,j} \quad \forall k \in K, r \in R, i, j \in N \tag{3.20}$$

Constraint (3.21) ensures that transshipments take place only once per transshipment terminal. Constraint (3.22) prohibits transshipment between the same vehicle.

$$s^{l,k}_{i,r} \leq 1 \quad \forall l, k \in K, r \in R, i \in T \tag{3.21}$$

$$s^{k,k}_{i,r} = 0 \quad \forall k \in K, r \in R, i \in T \tag{3.22}$$

Constraints (3.23-3.25) are used for subtour elimination.

$$x^k_{ij} \leq z^k_{ij} \quad \forall k \in K_b \cup K_t, \forall i, j \in N \tag{3.23}$$

$$z^k_{ij} + z^k_{ji} = 1 \quad \forall k \in K_b \cup K_t, \forall i, j \in N \tag{3.24}$$

$$z^k_{ij} + z^k_{jp} + z^k_{pi} \leq 2 \quad \forall k \in K_b \cup K_t, \forall i, j, p \in N \tag{3.25}$$

Constraints (3.26-3.31) are the temporal constraints. Constraints (3.26-3.30) 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 (3.31) sets time constraints for transshipment.

$$t_{r,i}^{arr,k} \leq t_{r,i}^{ss,k} \leq t_{r,i}^{se,k} \quad \forall k \in K \forall r \in R \forall i, j \in N \tag{3.26}$$

$$t_{r,i}^{ss,k} + t_{r,i}^{load,k} \sum_{j \in N} y_{ij}^{k,r} \leq t_{r,i}^{se,k} \quad \forall k \in K \forall r \in R \forall i, j \in N \tag{3.27}$$

$$t_{i}^{arr,k} \leq t_{r,i}^{arr,k} \quad \forall k \in K \forall r \in R \forall i, j \in N \tag{3.28}$$

$$t_{r,i}^{se,k} \leq t_{i}^{dep,k} \quad \forall k \in K, \forall r \in R, \forall i, j \in N \tag{3.29}$$

$$-M(1 - x_{ij}^{k}) \leq t_{i}^{dep,k} + t_{ij}^{k} + t_{j}^{arr,k} \leq M(1 - x_{ij}^{k}) \quad \forall k \in K, \forall i, j \in N, \tag{3.30}$$

$$t_{r,i}^{dep,k} - t_{r,i}^{se,l} \leq M(1 - x_{i,r}^{kl}) \quad \forall k, l \in K, k \neq l, \forall r \in R, \forall i \in T, \tag{3.31}$$

Constraints (3.32) and (3.33) define binary variables.

$$x_{ij}^{k} \in \{0, 1\} \quad \forall k \in K, \forall i, j \in N \tag{3.32}$$

$$y_{ij}^{kr} \in \{0, 1\} \quad \forall k \in K, \forall r \in R, \forall i, j \in N \tag{3.33}$$

For more detailed illustrations of the constraint, please refer to the research of Zhang et al. [4].

3.2.2 Solution algorithm

Previous papers have verified the ability of ALNS to produce (near) optimal solutions for vehicle routing problems and require relatively short computation time when dealing with large instances [4, 64, 12]. The classical STPM without shippers' preference can be solved by the ALNS algorithm proposed in the research of Zhang et al. [4]. To solve STPM-SP, Algorithm 1 is proposed, which is extended from [4]. The differences include 1) incorporating the shippers' satisfaction ($g(\theta)$) into the objective function; 2) assigning a higher acceptance probability to the solutions with better performance in terms of shipper satisfaction; 3) searching for Pareto solutions considering shippers' preferences. The input of Algorithm 1 includes vehicles (K), requests (R), terminals (N), and the satisfaction approximator $g(\theta)$. The output includes the Pareto solutions for STPM with shippers' preferences (X_p). In the search for Pareto solutions, n_p donates the label of Pareto solutions. $n_p = 1$ means the current solution is a non-dominated one and will be included in the Pareto set; X_{-x} represents the solution set excluding the solution x. The Pareto solutions will be provided to shippers to collect ranking feedback and then used for preference learning to update $g(\theta)$.

Algorithm 1 ALNS algorithm with shippers' preferences

Input: $K, R, N, I, g(\theta)$
Output: X_{pareto}

obtain the initial solution $X_{initial}$, and then $X_{last} \leftarrow X_{initial}$
initialize Tem, R_{pool}, X_p
for $i \leftarrow 1, I$ **do**
    Refresh weights and choose operators based on weights;
    $X_{current} \leftarrow X_{last}$
    while R_{pool} is not empty **do**
        $[X_{current}, R_{pool}] = RemovalOperator(X_{current}, R_{pool}))$
        $[X_{current}, R_{pool}] = InsertionOperator(X_{current}, R_{pool}))$
    end while
    if $c(X_{current}) < c(X_{last})$ and $U(X_{current}, g(\theta)) > U(X_{last}, g(\theta))$ **then**
        $X_{last} \leftarrow X_{current}$
    else if $c(X_{current}) < c(X_{last})$ and $U(X_{current}, g(\theta)) < U(X_{last}, g(\theta))$ **then**
        if $\frac{c(X_{last} - c(X_{current})}{c(X_{current}} < \frac{U(X_{last}, g(\theta)) - U(X_{current}, g(\theta))}{U(X_{last}, g(\theta))}$ **then**
            $X_{last} \leftarrow X_{current}$
        else if $c(X_{current}) > c(X_{last})$ and $U(X_{current}, g(\theta)) > U(X_{last}, g(\theta))$ **then**
            if $\frac{c(X_{current}) - c(X_{last})}{c(X_{current}} > \frac{U(X_{current}, g(\theta)) - U(X_{last}, g(\theta))}{U(X_{last}, g(\theta))}$ **then**
                $X_{last} \leftarrow X_{current}$
            else
                $X_{last} \leftarrow X_{current}$ with the probability $p = e^{(1 - \frac{U(X_{last}, g(\theta))}{U(X_{current}, g(\theta))}/Tem)}$
            end if
        end if
        $X = X \cup X_{last}$

        for $x \in X$ **do**
            $n_p = 1$
            for $x' \in (X_{-x})$ **do**
                if $c(x') < c(x)$ and $U(x', g(\theta)) > U(x, g(\theta))$ **then**
                    $n_p = 0$;
                    $break$;
                end if
            end for
            if $n_p = 1$ **then**
                $X_p = X_p \cup x$
            end if
        end for

3.3 Preference learning

This section introduces the preference learning method and discusses synthetic preference.

3.3.1 Preference learning algorithm

The goal of preference learning is to develop a model that predicts the utility of a given transport plan. The process of the learning algorithm is shown in Algorithm 2. The input of preference learning includes shippers' ranking results F, shippers' ID S, transport plans X with attributes, and the learning model with initialized parameters $g(\theta_0)$. Parameters include the epochs ep, batch size b, and learning rate rl for the training of neural networks. The output is the updated parameters of the neural network $\theta_{current}$.

After receiving the input, the first step is to initializing the utility estimator. Since the utility value is not directly observable in practice, this model learns from comparative preference information instead of the target scores of utilities. Before the model-training process, shippers' ranking feedback F is transformed into pairwise comparisons. For example, the ranking of the shipper s on three transport plans $(\lambda_i \succ_s \lambda_j \succ_s \lambda_k)$ can be transformed into three sets of preference relations: $(\lambda_i \succ_s \lambda_j), (\lambda_j \succ_s \lambda_k), (\lambda_i \succ_s \lambda_k)$. The task of the utility estimator is to regress the feature representation onto a real-valued utility using a mapping $g : X \to U$:

$$U = g(X, \theta) \tag{3.34}$$

where the input X is the set of model input features and θ is a set of parameters in the utility function approximator, and output U is the predicted utility value regarding the transport plan with attributes X.

This research proposes to incorporate the structure of artificial neural networks into preference learning and uses binary logit models as the baseline model. The purpose of this comparison is not to determine a definitive superior model, but rather to explore how each model adapts under different conditions and gain insights into the reasons for their respective performance. The experiments will compare the fundamental characteristics between statistical-based utility estimators and data-driven utility estimators. Binary logit models predefine the relationships between variables based on prior knowledge of utility. Artificial neural networks use interconnected layers of neurons to capture the patterns directly from data.

Binary logit model

The binary logit model is used as the baseline model of the utility estimator, which has been widely used for shippers' preference exploration [40]. In a pairwise comparison between transport plan i and transport plan j, the utility of shippers towards each plan can be determined based on various factors (Eq 3.35), including cost, time, delay, emissions, and transshipment involved in the transportation process. Additionally, a random factor is considered, following the Gumbel distribution, which introduces stochasticity into the utility estimation. The binary logit model assigns a probability to each alternative, indicating the likelihood of it being chosen. The probability of choosing transport plan i over transport plan j can be determined by Eq 3.36.In this research, the establishment and training of BLs are conducted using Biogeme on Python.

$$u_i = \beta_c c_i + \beta_t t_i + \beta_e e_i + \beta_d d_i + \beta_{tr} tr_i + \epsilon_i \tag{3.35}$$

$$p(i) = \frac{e^{u_i}}{e^{u_i} + e^{u_j}} \tag{3.36}$$

Artificial neural networks

Artificial neural networks have shown powerful estimation and prediction capabilities in travel behavior modelling[43, 59]. Specifically, Wang et al. [59] demonstrated that NNs tend to have smaller approximation errors than binary logit (BNL) and multinomial logit (MNL) models in choice analysis. In neural networks, fully-connected layers (or linear layers) are commonly used to connect every input neuron to every output neuron. The output of each layer can be calculated as Eq (3.37). Rectified linear units (ReLU) are used in deep learning models as activation function ψ. In the case of a negative input, it returns 0, and in the case of a positive input, it returns the same positive value. The function is written in Eq (3.38).

$$x_i = \psi(w_i x_{i-1} + b_i), \quad (i-1, i) \in I \tag{3.37}$$

$$\psi(x) = \max(0, x) \tag{3.38}$$

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 and b_i are the learned weights and learned bias term of layer i; I represents the set of layers.

This research designs two learning models for shippers' preference learning: artificial neural networks (NNs) for homogeneous preference learning and artificial neural networks with preference matrix (NN-PMs) for heterogeneous preference learning. Both models utilize the structure of artificial neural networks, with the output being the utility of specific transport plans. The main distinction between these two models lies in the input features. In NNs, the input features are the attributes associated with the transport plans. While NN-PMs incorporate not only the transport plan attributes but also the preference matrix of the shipper. The use of the preference matrix is to reflect the preferences of different shippers and enable more personalized utility estimation. The preference matrix is constructed based on shippers' previous choices and the comparison of transport attributes in these choices. Each row in the matrix corresponds to a shipper, and each column represents a specific count value for transport attributes. The entries in the matrix indicate whether the chosen transport plan has a lower value of each attribute for each shipper. The determination of the preference matrix is shown in Equation 3.39.

$$PM_n = [pc_n, pt_n, pd_n, pe_n, ptr_n] \tag{3.39}$$

where PM_n represents the preference vector for shipper n; $pc_n, pt_n, pd_n, pe_n, ptr_n$ 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 be plus 1, otherwise, it will be minus 1.

Training process

The task of training is to optimize parameters and find the function that can be as much as possible in line with shippers' comparisons. The optimization of model parameters can be divided into three steps: 1) estimating the utilities of transport plans; 2) computing the loss; 3) updating model parameters.

For each pairwise comparison, the information includes attributes of two transport plans, the shipper ID and the chosen transport plan. The learning model estimates the utility of each transport plan. The transport attributes are the input of NNs for the utility estimation. In cases where there is heterogeneity, the shipper ID is used to extract the preference matrix based on the historical choice data, as an additional input to NN-PMs. The shippers' pairwise comparison results are used as supervision for the learning process.

Considering the probabilistic nature of individual decision-making [74, 75, 76], the cross-entropy loss, so-called negative log-likelihood, is used to estimate the population error between the estimated utility comparison and the shippers' utility comparison. The loss function can be written as Eq 3.42:

$$L = -\frac{1}{N}\sum_{n=1}^{N}(y_n * \log(\frac{e^{U_{in}}}{e^{U_{in}} + e^{U_{jn}}}) + (1 - y_n) * \log(\frac{e^{U_{jn}}}{e^{U_{in}} + e^{U_{jn}}})) \tag{3.40}$$

where N is the number of training samples; U_{in} and U_{jn} are the utilities of the transport plan λ_{in} and λ_{jn}, respectively; y_n represents the ground-truth label of the shippers' choice, where $y_n = 1$ means the shipper prefers the transport plan λ_{in} over the transport plan λ_{jn}, $y_n = 0$ means the shipper chooses the transport plan λ_{jn}, and $y_n = 0.5$ means the utilities of λ_{in} and λ_{jn} are the same.

This research applies the backpropagation process to compute the gradient of the loss function with respect to each network parameter and uses the AdamW optimizer to optimize the parameters that minimize the loss. AdamW optimizer [77] is a stochastic optimization method that improves upon the standard Adam optimizer by decoupling weight decay from the gradient update process. Eq 3.41 shows the parameter updating using AdamW. By iteratively applying utility calculation, loss calculation, and backpropagation on a training dataset, the network's parameters are updated to minimize the error and improve the network's performance.

$$\theta_{t+1} = \theta_t - (\alpha\frac{m_t}{\sqrt{v_t} + \delta} + \lambda\theta_t) \tag{3.41}$$

where θ_t denotes the parameters of the artificial neural network at iteration t, and θ_t denotes the updated parameters for the next iteration. θ collectively denotes weights w and bias b. m_t is the first moment vector and v_t is the second moment vector.δ is a small positive value; λ is the rate of weight decay (0.01).

Algorithm 2 Preference learning algorithm

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

Initialize θ_0
for $i \leftarrow 1, n$ **do**
  $[x_i, x_j, y] \leftarrow transformation(X, F, S, i)$ ▷ Transform ranking 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 if $\hat{u_i} < \hat{u_j}$ **then**
    $\hat{y} \leftarrow 0$ ▷ Choose x_j over x_i
  else $\hat{u_i} = \hat{u_j}$
    $\hat{y} \leftarrow 0.5$
  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
  $\theta_{n+1} = update\_parameters(\theta_n, \frac{\partial L_n}{\partial \theta_n}, lr)$ ▷ Update the utility estimator
end for
$\theta_{current} \leftarrow \theta_n$ =0

3.3.2 Synthetic preference

In the proposed framework, shippers are asked to rank transport plans provided by the freight forwarder. This research uses synthetic preference data for model evaluation due to several reasons: firstly, synthetic data can simulate "what if" scenarios of shippers' preferences, allowing this research to test the capacity of the proposed models under various conditions (i.e., homogeneity, heterogeneity, linearity, nonlinearity). Second, the scalability of synthetic data can provide sufficient samples for model testing and examine the performance of the proposed models at different scales of dataset. For this research, the collection of feedback data during the actual transport process can be challenging. The preference data collection can involve privacy concerns and the confidentiality of business-sensitive information. Considering the factors discussed above, the utilization of synthetic data is a suitable and feasible option.

Random utility maximization hypothesis has been widely used in transport decision-making [27, 21], using the utility to represent the willingness to choose. It assumes that shippers would choose the alternative that maximizes their utility. Considering the decision-making process between two alternative transport plans (λ_i, λ_j), the utility can justify as shippers' criterion for ranking given transport plans, as shown in the following relation:

$$\lambda_i \succ \lambda_j \Leftrightarrow U(\lambda_i) > U(\lambda_j) \tag{3.42}$$

where $U(\lambda_i)$ and $U(\lambda_j)$ represent the utility of the alternative i and the alternative j, respectively. Synthetic data of shippers' ranking is generated using the above decision-theoretic setting.
The utility of each alternative i is composed of a systematic utility V_i and a random utility ϵ_i (in Eq (3.43)). The systematic one is determined by observable features of the transport alternative. The random utility represents the unobserved features and tastes, considering the stochastics in the decision-making process.

$$U_i = V_i + \epsilon_i \tag{3.43}$$

Systematic utility

This research considers both linearity and nonlinearity in utility functions. Linear utility functions have been commonly used in previous research [27].

$$V_i^1 = \beta_c c_i + \beta_t t_i + \beta_e e_i + \beta_d d_i + \beta_{tr} tr_i \tag{3.44}$$

For the nonlinear specification of the systematic utility function, this research refers to the work of Jensen et al. [39]. Jensen et al. [39] considered the nonlinearity in piecewise function, and the use of the natural logarithm $ln(x)$ suggested that the effect of attributes could be incremental. Therefore, this research adopts the nonlinear systematic functions as shown in Eq(3.45).

$$V_i^2 = \beta_c F(c_i) + \beta_t F(t_i) + \beta_e e_i + \beta_d d_i + \beta_{tr} tr_i \tag{3.45}$$

$$F(x) = \begin{cases} \ln(x)^3 & if \quad 0 < x \leq c_1 \\ a_1 \ln(x)^2 + b_1 & if \quad c_1 < x \leq c_2 \\ a_2 \ln(x) + b_2 & if \quad c_2 < x \end{cases} \tag{3.46}$$

The parameters in Eq(3.45) are set based on the research of Jensen et al. [39]: $c_1 = 100/3$,$c_2 = 2 * 100/3$, $a_1 = \frac{2}{3}\ln(c_1)\ln(c_2)$, $b_1 = -0.5(\ln(c_1))^3$ and $b_2 = -0.5(\ln(c_1)[3(\ln(c_2))^2 + 3(\ln(c_1))^2]$. The connectivity and continuity of the cost curve were demonstrated in the work of Rich [78].
Both linear and nonlinear utility functions in Eq (3.44,3.45) will be used (separately) to generate the synthetic preference to test the performance of preference learning methods.

Considering the shippers' preferences can be heterogeneous, Shippers can have different prioritization on transport attributes. To represent the prioritization, weights are assigned to transport attributes, which are α_c, α_t, α_e, α_d, and α_{tr}. The heterogeneous systematic utility for linear functions and nonlinear functions can be written as follows:

$$V_i^{h1} = \alpha_c \beta_c c_i + \alpha_t \beta_t t_i + \alpha_e \beta_e e_i + \alpha_d \beta_d d_i + \alpha_{tr} \beta_{tr} tr_i \tag{3.47}$$

$$V_i^{h2} = \alpha_c \beta_c F(c_i) + \alpha_t \beta_t F(t_i) + \alpha_e \beta_e e_i + \alpha_d \beta_d d_i + \alpha_{tr} \beta_{tr} tr_i \tag{3.48}$$

Random utility

For the random utility, this research uses a standard Gumble distribution for ϵ, which is a type I extreme value distribution with a location parameter equal to 0 and a scale parameter equal to 1. The equation for the standard Gumbel distribution can be written as:

$$f(x) = e^x e^{-e^x} \tag{3.49}$$

3.3.3 Evaluation criteria

To evaluate the prediction of proposed models, the prediction accuracy and the log loss are used as the evaluation criteria. The prediction accuracy is represented by the proportion of pairwise comparisons that are correctly predicted, which can be calculated using Eq. 3.50.

$$acc = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{3.50}$$

where $\hat{y}_i$ and y_i are the predicted label and the true label, respectively; N represents the total number of tested pairwise comparisons.

The log loss can be calculated according to Eq. 3.51. The log-loss metric quantifies the divergence between the predicted probability and the actual value. A higher log-loss value indicates a greater deviation between the predicted probability and the true value.

$$L = -\frac{1}{N}\sum_{n=1}^{N} (y_n * \log(p) + (1 - y_n) * \log(1 - p)) \tag{3.51}$$

where N represents the total number of tested pairwise comparisons; y_n is the true label of the sample n; p is the predicted probability that $y_n = 1$.

3.3.4 Model explaination

SHAP (SHapley Additive exPlanations) has been widely used to explain the output of artificial neural networks in multiple fields, such as image classification and natural language processing. This method, first proposed by Lundberg and Li [79] in 2017, is based on cooperative game theory. SHAP calculates the importance of features by comparing the differences between the prediction with the quality and the prediction without the feature, across all possible combinations of features. In Eq. 3.52, the sum of the SHAP values corresponds to the difference between the expected value and the prediction.

$$\sum_{i \in F} \phi_i(f, x) = f(x) - \mathbb{E}(f) \tag{3.52}$$

where $f(x)$ is the predicted value with all features; $\mathbb{E}(f)$ is the expeted value; $\phi_i(f, x)$ is the SHAP value for feature i. Lundberg and Li [79] have demonstrated the ability to produce consistent and reliable explanation results by comparing the performance of SHAP and other popular methods (i.e., local interpretable model-agnostic explanations (LIME), Deep Learning Important Features (DeepLIFT)). This section discusses how SHAP can be used to explain the prediction results and the differences with the explanation of binary logit models.

In heterogeneous scenarios, this research integrates a preference matrix into the artificial neural network structure, however, SHAP may not be suitable for explaining heterogeneity as it calculates the direct marginal impact of features to the expected value and is limited to capturing interactive variable relationships.

Chapter 4

Results

This chapter consists of three parts. The first section presents the experiment overview including the experimental framework, scenario design, and experiment settings. The second section compares the performance of preference learning methods in four preference scenarios. The third part evaluates the proposed synchromodal transport planning method and investigates the potential trade-off between planning objectives.

4.1 Overview of experiments

4.1.1 Experimental framework

Figure 4.1 shows the framework of experiments. This research designs different scenarios that consider homogeneous and heterogeneous preferences, as well as linearity and nonlinearity in true preferences. The proposed preference learning models with the structure of artificial neural networks will be examined. The classical discrete choice model, the binary logit model with linear model specification, is used as the baseline learning model. For synchromodal transport planning, this research implements STPM-SP to assign vehicles and routes to requests, using STPM as the baseline model.

The aim of experiments for preference learning is to compare the effectiveness of classical binary models and deep neural networks in 1) modeling the relationship between transport service attributes and shipper satisfaction (utility); 2) the ability to extract the information in the preference matrix into the learning process. Specific research questions related to preference learning will be answered, including: 1) How effectively can learning models capture preferences from shippers' feedback? 2) What are the performance differences between baseline models (BLs), artificial neural networks (NNs), and NNs with preference matrix (NN-PMs)? 3) How does the sample size impact the performance of preference learning?

The aims of experiments for synchromodal transport planning with shippers' preferences are 1) to assess the efficiency of synchromodal transport planning model with shippers' preference (STPM-SP) in improving transport services compared to the traditional STPM; 2) to examine the impact of incorporating shippers' preferences into the planning process. These experiments target specific questions including: 1) How do Pareto solutions improve overall transport planning and do these improvements vary among shippers (classes) ? 2) What are the trade-offs involved in improving shippers' satisfaction and other transport attributes? 3) How will the mode share change in these solutions?

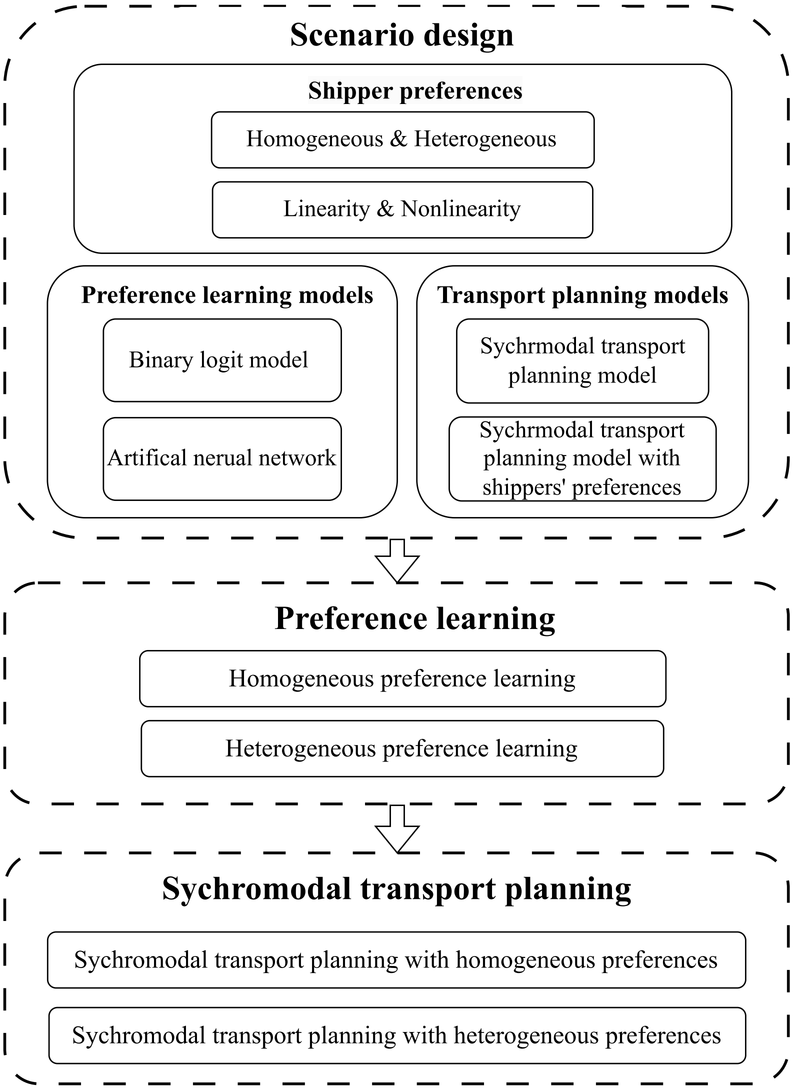


Figure 4.1: The framework of experiments

4.1.2 Scenario design and synthetic preferences

Considering homogeneous preferences and heterogeneous preferences, homogeneous preferences mean that all shippers have the same preferences for transport plans, that is, the utility functions of all shippers are identical. Heterogeneous preferences consider shippers have different preferences for transport attributes. In this research, four classes of true preferences are predefined, with each shipper belonging to one of these classes. Table 4.1 presents an overview of designed scenarios.

Table 4.1: Overview of experiment scenarios

Scenarios		Preference	True utility function	Models
Scenario 1	HoS1	Homogeneous	Linear	BL, NN
	HoS2	Homogeneous	Nonlinear	BL, NN
Scenario 2	HeS1	Heterogeneous	Linear	BL, NN, NN-PM
	HeS2	Heterogeneous	Nonlinear	BL, NN, NN-PM

Table 4.2 shows the specific utility functions used in each scenario. In the homogenous scenario, two sub-scenarios are designed: Homogenous Scenario 1 (HoS1) represents the case where the true preferences follow a linear utility function, and in Homogenous Scenario 2 (HoS2), the true preferences follow a nonlinear utility function. In the heterogeneous scenario, four classes of true preferences are predefined based on the shipper classification result in the research of Khakdaman et al. [26]: 1) high service-level shippers (35.9%): these shippers look for improvements in service levels, particularly in minimizing time and delay; 2) cost-sensitive shippers (32.3%): these shippers are sensitive to the cost. They are willing to take risks and longer time for the cost reduction in return; 3) eco-conscious shippers(18.4%): these shippers tend to minimize the environmental impact of their shipping activities (emission); 4) cost-efficient shippers (13.4%): these shippers are willing to make trade-offs and try to minimize delay and cost in their shipping operations simultaneously.

Table 4.2: The specification of utility functions in homogenous scenarios

Scenario	Model specification	Parameters
HoS1	Equation 3.44	$\beta_c = 10, \beta_t = 8, \beta_d = 5, \beta_e = 5, \beta_{tr} = 2$
HoS2	Equation 3.45	$\beta_c = 10, \beta_t = 8, \beta_d = 5, \beta_e = 5, \beta_{tr} = 2$ $c_1 = 100/3, c_2 = 2 * 100/3,\ a_1 = \frac{2}{3}\ln(c_1)\ln(c_2),\ b_1 = -0.5(\ln(c_1))^3$ $b_2 = -0.5(\ln(c_1)[3(\ln(c_2))^2 + 3(\ln(c_1))^2]$
HeS1	Equation 3.47	$\beta_c = 10\alpha_c, \beta_t = 8\alpha_t, \beta_d = 5\alpha_d, \beta_e = 5\alpha_e, \beta_{tr} = 2\alpha_t r$
HeS2	Equation 3.48	$\beta_c = 10\alpha_c, \beta_t = 8\alpha_t, \beta_d = 5\alpha_d, \beta_e = 5\alpha_e, \beta_{tr} = 2\alpha_t r$ $c_1 = 100/3, c_2 = 2 * 100/3,\ a_1 = \frac{2}{3}\ln(c_1)\ln(c_2),\ b_1 = -0.5(\ln(c_1))^3$ $b_2 = -0.5(\ln(c_1)[3(\ln(c_2))^2 + 3(\ln(c_1))^2]$

Table 4.3: Shipper classes in heterogeneous scenarios

Class	Parameters
Class 1	$\alpha_c = 1, \alpha_t = 10, \alpha_d = 10, \alpha_e = 1, \alpha_{tr} = 1$
Class 2	$\alpha_c = 10, \alpha_t = 1, \alpha_d = 1, \alpha_e = 1, \alpha_{tr} = -1$
Class 3	$\alpha_c = 1, \alpha_t = 1, \alpha_d = 1, \alpha_e = 10, \alpha_{tr} = 1$
Class 4	$\alpha_c = 1, \alpha_t = 5, \alpha_d = 5, \alpha_e = 1, \alpha_{tr} = 1$

It is important to note that the discussion of the performance of BLs is limited to the specific model used, as described in Section 2. The model assumes linear relationships between transport attributes and utilities, and the model specification (3.35) represents utility as a linear combination of transport attributes with a random term. However, within the field of shippers' preference research, there are various specifications for discrete choice models. For example, logarithms can be integrated into the model specification for modeling nonlinearity. The latent class discrete choice model can account for different groups of shippers. The performance of these alternative models may differ from the baseline models utilized in this research. However, when selecting the appropriate model specification, careful consideration of the functional forms, assumptions, and interactions among variables is necessary. It requires validation and evaluation using statistical techniques to ensure the chosen model can accurately represent the underlying preferences.

4.2 Experiments on preference learning

This section first presents the data preparation process and the statistics of samples, then the performance of proposed preference learning models and baseline models are evaluated in scenarios designed in Section 4.1.2. The prediction results are explained by analyzing the impacts of transport attributes on the choices of shippers.

4.2.1 Transport network and data preparation

This research uses the European Gateway Services (EGS) network to conduct experiments for model valuation. EGS network is located at Rhine-Alpine corridor, providing connections between the ports of Rotterdam, Antwerp and the prominent economic hubs in Western and Central Europe. As shown in Figure 4.2, there are 10 terminals within the network with 3 deep-sea terminals located in the Port of Rotterdam and 7 inland terminals in the Netherlands, Belgium, and Germany. Additionally, there are 10 transshipment terminals that facilitate cargo transfer between different transportation modes. The instances comprise a total of 116 vehicles, including 49 barges, 33 trains, and 34 trucks. The specific parameters related to vehicles are shown in Table C.1 in the Appendix. Before transport planning, requests are generalized by randomly selecting the origin terminal p_r, destination terminal d_r, pickup window $[a_{p(r)}, b_{p(r)}]$, drop-off window $[a_{d(r)}, b_{d(r)}]$, and the load of containers q_r. The requests' origins and destinations are randomly distributed among deep-sea terminals and inland terminals, respectively. The container volumes of the requests are independently drawn from a uniform distribution with a range of [10, 30] TEU. Additionally, the earliest pickup time for the requests is independently drawn from a uniform distribution ranging from 1 to 120. The latest delivery time is 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 the range of hours [20,80].

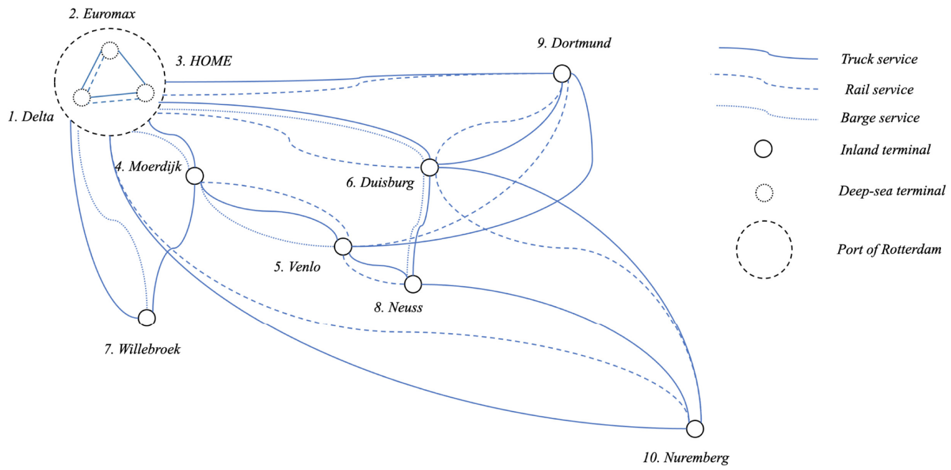


Figure 4.2: The European Gateway Services network [1]

To prepare the shippers' feedback data from preference learning, this research conducts 30 instances of the synchromodal transport operations and simulates the ranking process of shippers using utility functions predefined in synthetic preference. It is assumed that there are 100 shippers in total in this system. In a single instance of planning, a shipper could have no request or have one or multiple requests. The freight forwarder receives 100 to 200 requests. After receiving shipping requests, the freight forwarder will use the STPM to propose transport plans (assigning vehicles and routes) for each request without the consideration of shippers' preferences. It is assumed that the freight forwarder will serve all the received requests. To collect ranking information from shippers, the freight forwarder selects the top five lowest-cost solutions. Next, the transport plans within each solution are assigned to corresponding shippers with calculated transport attributes. Then, the freight forwarder asks shippers to rank the provided alternatives according to their preferences. Since there are no actual shippers involved in the research, the choices are simulated by calculating the utility of each solution using the predefined utility function and ranking transport alternatives based on respective utility values.

Table 4.4 shows the statistics information of all the transport plans provided with sippers. The transport planning operations generated 4777 transport plans after removing the duplicated ones. The transport attributes (i.e., cost, time, delay, emission, and transshipment) for these plans can be calculated based on Equation 3.9-3.13. The mean values and 75th percentiles of all the attributes are less than 0.500. Cost, emission, and transshipment have larger standard deviations than time and delay, indicating greater variability in these attributes

Table 4.4: Summary statistics of transport plans

Variables	Mean	Std	Min	25%	50%	75%	Max
Cost	0.491	0.648	0.194	0.231	0.293	0.457	4.579
Time	0.188	0.157	0.013	0.091	0.141	0.237	1.294
Delay	0.040	0.187	0.000	0.000	0.000	0.000	3.543
Emission	0.497	0.844	0.210	0.229	0.243	0.308	5.682
Transshipment	0.213	0.647	0.000	0.000	0.000	0.000	2.900

After the simulation of shippers ranking the assigned transport plans, the ranking results are reorganized in the form of pairwise comparisons, generating more than $70,000$ pairs of pairwise comparisons for training and testing of preference learning models. In each pairwise comparison, two alternatives (transport plans) are put in two columns, C_0 and C_1, respectively. Such a transport plan pair is one sample point for model estimation, specifically, binary logit models and artificial neural networks are trained based on estimating the respective utilities of two transport plans and then comparing the utility values to optimize model parameters. Table 4.5 shows the statistics of pairwise comparisons generated based on the 100 shippers ranking their transport plans in 30 instances of transportation operations. On average, one shipper needs to rank seven transport plans for the data collection. $N(C_0)$ and $N(C_1)$ are the percentages of transport plans being chosen in columns C_0 and C_1, respectively. As the true preferences are different in the pre-defined four scenarios (i.e., HoS1, HoS2, HeS1 HeS2), the values of $N(C_0)$ and $N(C_1)$ in the four scenarios can be different. As the parameters of models are optimized by the comparisons of transport plans in $N(C_0)$ and $N(C_1)$, it ensures that the choices in both sets are balanced for model training. S(HoS1), S(HoS2), S(HeS1) and S(HeS2) are the percentage of choices change comparing to scenarios HoS1, HoS2, HeS1 and HeS2, respectively. It can be observed that the difference in choice between the linear and nonlinear utility functions is greater than the difference between homogeneous and heterogeneous preferences.

Table 4.5: Statistics of shippers' choices in four scenarios

Scenario	$N(C_0)$	$N(C_1)$	S(HoS1)	S(HoS2)	S(HeS1)	S(HeS2)
HoS1	0.501	0.499	0	21813	6550	22690
HoS2	0.486	0.514	21813	0	21651	4209
HeS1	0.499	0.501	6550	21651	0	22352
HeS2	0.485	0.516	22690	4209	22352	0

As for the models, in preference learning, a 5-layer artificial network is used with $5*64$ neurons in the input layer,$64*64$ neurons in hidden layers, and $64*1$ neurons in the output layer. The ReLU function is used as the activation function. As the ranking data is transformed into pairwise comparisons, therefore, the binary logit model is used as the benchmark.

4.2.2 Model comparison

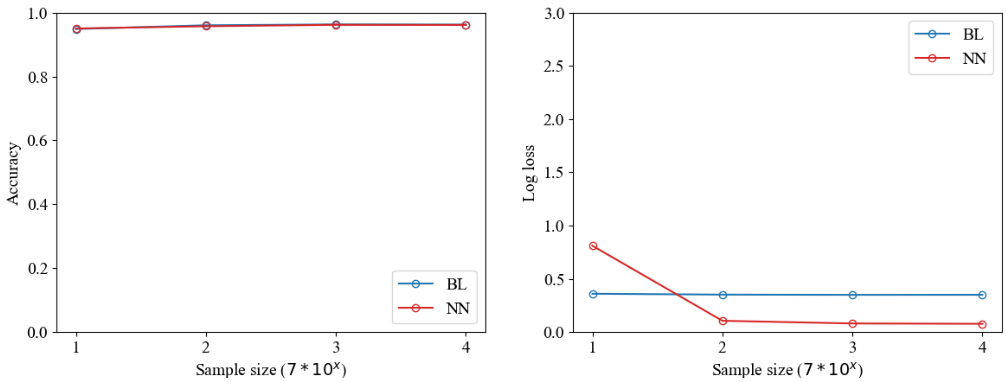
This section has homogeneous preferences and heterogeneous preferences. Each part has two sub-scenarios, one using linear true utility functions, and the other using nonlinear utility functions.

The performance of the models is evaluated based on two criteria, prediction accuracy and log loss. Log loss (also called the negative log-likelihood loss) represented the difference between the predicted probability distribution and the actual probability distribution. Lower log loss indicates better preference probability prediction. The log loss is normalized by dividing by the sample size, which ensures that the value is comparable with different numbers of samples.

Scenario 1: Homogeneous preferences

When assuming shippers have identical preferences, the behaviors of shippers will follow the same utility function. In HoS1 and HoS2, a linear function and a nonlinear function are employed as true utility functions, respectively. Binary logit models (BL) and artificial neural networks (NN) are tested as utility estimators with various training sample sizes. In HoS1, the true utility function is based on the linear combination of transport attributes (i.e., cost, time, delay, emission, transshipment), therefore, binary models correctly specify the true preference function. In HoS2, model specification in BL cannot fully capture true preferences due to the nonlinear relation between transport attributes.

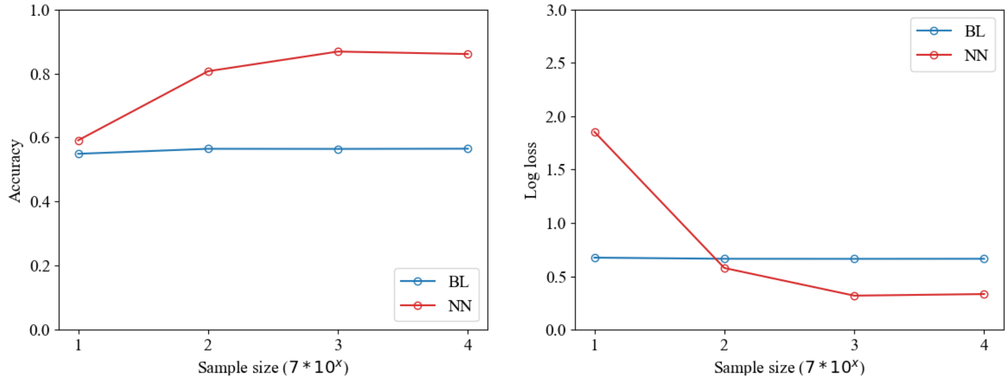
Figure 4.3 shows the accuracy and the log loss of prediction results of BLs and NNs in the scenario of HoS1. For both BLs and NNs, the prediction accuracy can reach above 90%, and slightly improves with the increase of sample size. The reason for the high prediction accuracy could be due to BLs having the correct model specifications that match the actual preferences, and the neural networks' capability to model the linear correlation between transportation attributes and utilities. In addition, NNs have a higher log loss than BLs with a small sample size (70), while obtaining lower log loss with sample sizes of $7 * 10^2, 7 * 10^3, 7 * 10^4$, which is in line with the results in the research of Wang et al.[59].



(a) Accuracy (b) Log loss

Figure 4.3: Evaluations of utility predictions in HoS1

In HoS2, the utility has nonlinear relationships with the transportation attributes. As shown in Figure 4.4, both models exhibit an accuracy of less than 60% with a sample size of 70, while the accuracy of NNs is slightly higher than BLs. As the sample size increases from $7 * 10^1$ to $7 * 10^3$, the prediction accuracy of NNs improves significantly, reaching 85% with $7 * 10^3$ samples, while the accuracy of BLs remains below 60%. This is due to the fixed model specification of BLs, which cannot handle nonlinearity in the data, whereas NNs can use nonlinear activation functions to model complex nonlinear relationships. It should be noted that a relatively large sample size is required for NNs to capture the nonlinearity, which is $7 * 10^3$ in this case. Similar to HoS1, the log loss of NNs is higher than BLs when the sample size is small, but it decreases substantially as the sample size grows.



(a) Accuracy (b) Log loss

Figure 4.4: Evaluations of utility predictions in HoS2

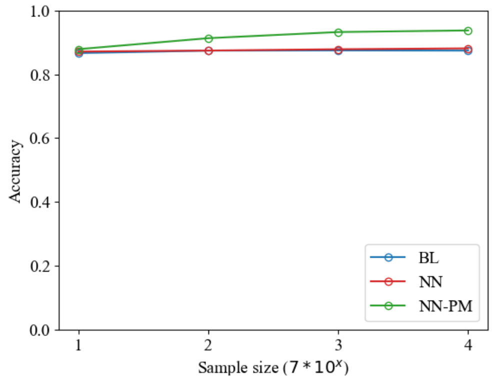
Scenario 2: Heterogeneous preferences

Scenario 2 examines a more realistic and complex setting where shippers' preferences can be heterogeneous. To represent these preferences, the research uses four shippers' classes based on previous literature, as shown in Section 4.1.2. Three models are tested in this section: binary logit models (BL), artificial neural networks with transport attributes as input (NN), and artificial neural networks with both transport attributes and preference matrix as input (NN-PM). The comparison between BLs and NNs can reveal differences in predictive ability resulting from model specifications and direct learning of nonlinearity from data. The comparison between NNs and NN-PMs can demonstrate the impact of incorporating the preference matrix in choice prediction.

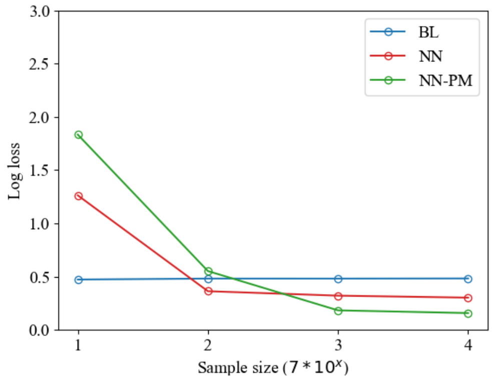
HeS1 considered the scenario that shippers have heterogeneous preferences and the true utility function is linear combinations of transport attributes. As shown in Figure 4.5, all three models can achieve an accuracy of over 80%. As the sample size increases, the accuracy of NN-PMs increases to 90%, while the changes in BLs and NNs are insignificant. This can be because the preference matrix reflects the priority from past choices made by shippers, and the architecture of artificial neural networks captures these priorities and construct utility functions that can predict new choices considering the respective preferences of shippers. When the sample size is $7 * 10^1$ or $7 * 10^2$, the log loss of NN-PMs is higher than that of both NNs and BLs, but it decreases to the lowest level when the sample size reaches $7 * 10^4$. This suggests that with a larger number of comparison samples, the information in the preference matrix becomes more reliable for distinguishing between different classes of shippers.

HeS2 considers the heterogeneous preferences with the true utility functions being nonlinear. The accuracy of BLs remains below 60% with the sample size ranging from $7 * 10^1$ to $7 * 10^4$, as the model specification being incapable of capturing the nonlinearity and heterogeneity from data. The accuracy of NN-PMs is similar to that of NNs when the sample size is $7 * 10^1$, and it becomes slightly higher than NNs as the sample size increases. This improvement can be due to the fact that only a small proportion of shippers change their choices in heterogeneous scenarios compared to homogeneous scenarios, as shown in Table 4.5. The log loss of NNs and NN-PMs have lower values than BLs when the sample size is large $(7 * 10^3, 7 * 10^4)$.

To investigate the prediction results for each class of shipper, Figure 4.7 shows the shipper classification and prediction results in the scenario of heterogeneous preferences with a sample size of 7000 alternative comparisons. Figure 4.7a presents the relative importance of each attribute in the true preference in the case of HeS1. Figure 4.7b shows the percentages of predicted shippers in classes. NN-PM outperforms both BLs and NNs in both HeS1 and HeS2. In HeS1, NN-PMs have an accuracy of 97.12%, compared to 88.14% for BLs and 87.92% for NNs. In HeS2, the accuracy of BLs and NNs is significantly lower in HeS2 compared to HeS1. The accuracy of BLs

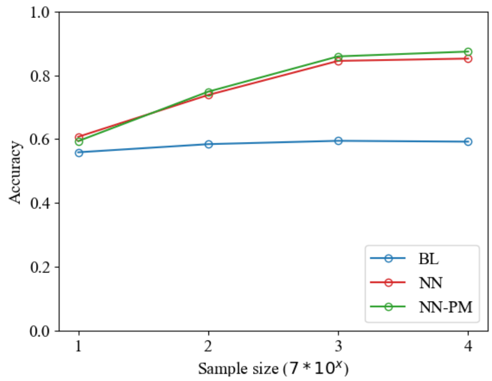


(a) Accuracy

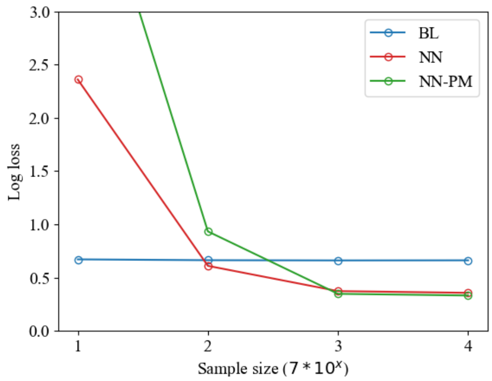


(b) Log loss

Figure 4.5: Evaluations of utility predictions in HeS1



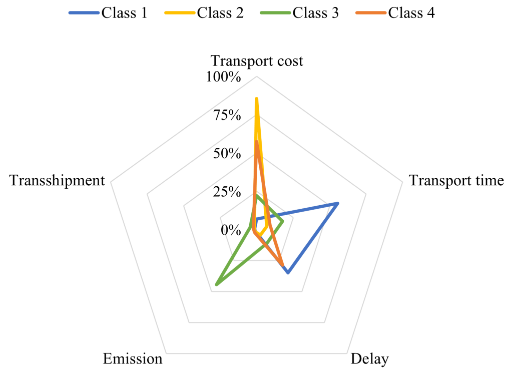
(a) Accuracy



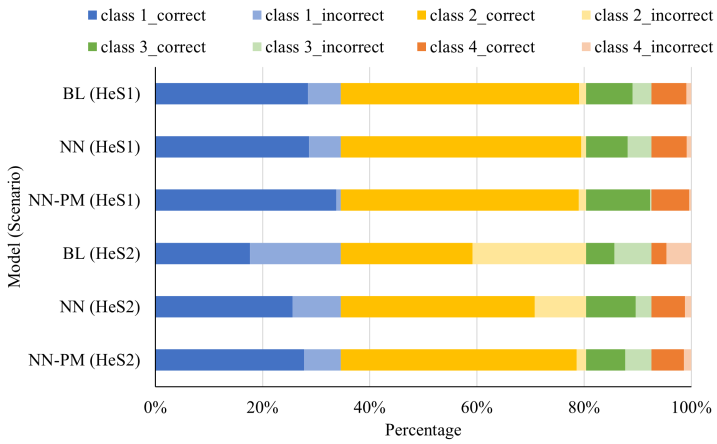
(b) Log loss

Figure 4.6: Evaluations of utility predictions in HeS2

decreases to 50.34% due to the inability to capture nonlinearity and heterogeneity in preferences. The accuracy of NNs decreases to 77.36%, suggesting that this model fails to distinguish differences across shipper classes. NN-PMs have an accuracy of 85.22%, higher than BLs and NNs. It can be observed that the percentages of incorrectly predicted choices in class 1 and class 3 are larger than those in class 2 and class 4. NN-PMs can correctly predict more shippers from class 1 and class 3 compared to BLs and NNs, which becomes the main factor in its overall better performance in HeS1. In HeS2, compared with NNs, NN-PM performs better in class 1 and class 2, while making more incorrect predictions in class 3. Compared with the results of NN-PM in HeS1, NN-PMs produce more incorrect predictions in class 1 and class 3, while having similar correctly predicted choices for class 2. These findings can be explained by the fact that shippers of class 2 place a greater priority on specific attributes (cost), compared to shippers in class 1 and class 3, as shown in Figure 4.7a, therefore, the preference matrix used in NN-PM can reflect the underlying preferences more accurately when the preference for specific attributes is stronger, allowing the deep neural network structure to better incorporate this information in its predictions. The specific percentages are listed in Table B.3



(a) Shipper class



(b) The percentages of predicted shippers in classes

Figure 4.7: Shipper classification and prediction results in the scenario of heterogenous preferences

4.2.3 Summary of model comparison

The increase in sample size can generally decrease prediction errors, and artificial neural networks are particularly sensitive to changes in sample size. This is because artificial neural networks are designed to learn directly from data, without relying on pre-defined model specifications. It is important to note that the improvement of NNs becomes slower 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, which is in line with the result of previous research[59]. For instance, in the case of the NNs model, the sample size required to achieve high performance can be dependent on the specific scenario and the shippers' real preferences. Specifically, in HoS1 and HeS1, the high performance of NNs was achieved with a sample size of $7 * 10^2$, and further increasing the sample size did not result in significant performance gains in terms of both accuracy and log loss. However, in HoS2 and HeS2 scenarios, the threshold value is found to be $7 * 10^3$.

In addition, Scenario HeS1 revealed that artificial neural networks with different inputs require different sample sizes to achieve optimal performance. It can be seen in Figure 4.5a and 4.5b that NNs can achieve the best performance with a sample size of $7 * 10^2$, while NN-PMs required a larger sample size of $7 * 10^3$. This difference can be explained that the incorporation of the information preference matrix can make artificial neural networks to be more effective in leveraging large datasets in scenarios where shippers' preferences are heterogeneous.

Table 4.6 shows the numerical results of prediction accuracy and log loss in terms of models and scenarios with the sample size being $7 * 10^4$. It can be observed that both BLs and NNs have both high accuracy in HoS1. BLs can efficiently capture shippers' preferences when the structures of model specification and the real preferences are the same. Considering Scenario HoS2, NNs outperform BLs by about 52.3% prediction accuracy, implying that the structure of NNs is more effective in capturing the nonlinearity in preference datasets.

In scenarios with heterogeneous preferences, NN-PMs outperform BLs and NNs in terms of both accuracy and log loss. This can be attributed to the incorporation of the preference matrix, which reflects shipper heterogeneity based on their previous choices. The architecture of artificial neural networks is capable of modeling and capturing this heterogeneity, leading to improved performance in predicting choice probabilities.

Table 4.6: The evaluation of models in four scenarios

Evaluation	Prediction Accuracy				Log Loss			
	HoS1	HoS2	HeS1	HeS2	HoS1	HoS2	HeS1	HeS2
BL	96.23%	56.51%	87.40%	59.21%	0.3506	0.6644	0.4827	0.6622
NN	96.12%	86.06%	88.10%	85.21%	0.0778	0.3340	0.3026	0.3569
NN-PM	-	-	93.71%	87.40%	-	-	0.1577	0.3321

It is important to note that the discussion of the performance of BLs is limited to the specific model used, as described in Section 3.3.1. The model assumes linear relationships between transport attributes and utility, and the model specification (Eq. 3.35) represents utility as a linear combination of transport attributes with a random term. However, within the field of shippers' preference research, there are various specifications for discrete choice models [38, 39, 19, 37]. For example, Box–Cox transforms [38] or logarithms [39] can be integrated in the model specification for modeling nonlinearity. The latent class discrete choice model can account for different groups of shippers [37, 19]. The performance of these alternative models may differ from the baseline models utilized in this research. However, when selecting the appropriate model specification, careful consideration of the functional forms, assumptions, and interactions among variables is necessary. It requires validation and evaluation using statistical techniques to ensure the chosen model can accurately represent the underlying preferences. In comparison, artificial neural networks can autonomously capture underlying relationships from the data. The neural network structure can provide opportunities to simplify the preparation work for model specification, enhance prediction accuracy, and reduce the risk of inappropriate specification. Furthermore, artificial neural networks may adapt to new data and identify patterns that may not be easily discerned using conventional statistical methods.

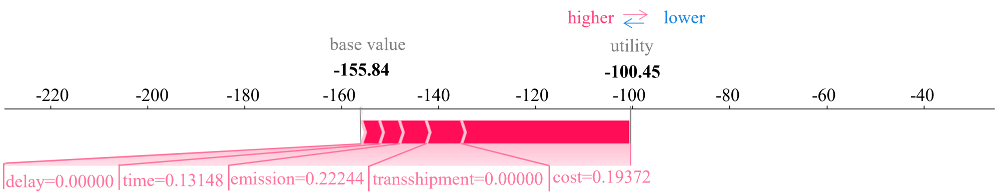
4.2.4 Model explanation

Homogeneous scenario

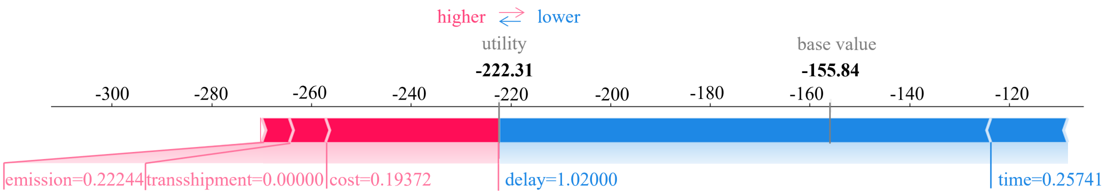
To understand how SHAP can explain individual preference, this section investigates the differences in the predicted utility and SHAP values on two alternatives (transport plan A and transport plan B). The force plots are shown in Figure 4.8a and 4.8b. The predicted utilities for transport plan A and transport plan B are -100.45 and -222.31, respectively. Therefore, shippers prefer transport plan A to transport plan B as utility A is higher. The base value is the expected utility prediction without input features, which is estimated by the average predicted utility. The base value, in this case, is -155.84. The willingness of shippers to choose transport plan A ($-100.45 > -155.84$) is higher than the average level of willingness, whereas transport plan B ($-222.31 < -155.84$) indicates the opposite. Taking the base value as the starting point, the colored bars in Figure 4.8a and 4.8b show the contributions of transport attributes (i.e., cost, time, delay, emission, transshipment) to the predicted utilities. Blue factors make the predicted utility less than the base value, and the red factors have a positive impact on a larger predicted utility than the base value. The values for each attribute are shown below the colored bars.

For the predicted utility of transport plan A, the cost of 0.194 has the largest effect to make the utility larger than the base value (-155.84), followed by transshipment. It is noted that although the value of transshipment is 0.000 in transport plan A, it has a positive impact on the predicted utility. This is because the base value is the reference with the information of all the values of transshipment in transport plans. Considering the transshipment can not be negative, the value of 0.000 represents a relatively low level of transshipment. It is consistent with the true utility function that transshipment has a negative parameter, so the lower transshipment contributes to a higher predicted utility.

For transport plan B, cost, transshipment, and emission have positive impacts on increasing the utility, while transport delay and transport time have distinct impacts on pushing the utility lower than the base value. Comparing plan A and plan B, it can be observed that the predicted utility of plan A is greater than the base value, while the predicted utility of plan B is lower. This can be attributed to the positive impact of a time value of 0.131 on the utility of plan A and the negative impact of a time value of 0.257 on the utility of plan B. The delay of 1.020 in plan B is the major reason for the lower utility. These findings are consistent with the true utility function, in which the increase in delay and time can decrease the utility.



(a) The utility for transport plan A



(b) The utility for transport plan B

Figure 4.8: Force plots for utility predictions in HoS1

Heterogeneous scenario

Based on the training of NN-PMs in the case of heterogeneous linear preferences, utilities for different types of shippers on the same transport plans can be calculated. To investigate the impact of attribute variance on utilities, utilities were first calculated by shipper class on the average transport plan, where attribute values were set to their average values. Next, utilities were calculated again after increasing respective attributes by 0.001, 0.010, and 0.100 to obtain the utility differences (the original utility minus the new utility).

Table 4.7 presents the resulting changes in utility values for each attribute by shipper class. These utility changes can provide valuable insights into the relative importance of different attributes for different classes of shippers. For example, shippers in Class 2 have the most significant negative impact among all classes with the increase in transport time, indicating this class is the most sensitive to transport costs, followed by Class 4, Class 3, and Class 1.

With the various values of transport attributes, the linearity in shippers' preferences can be observed from the changes in predicted utilities. The proportion of input changes is similar to the proportion of the output changes for all attributes. For instance, when the transport cost increases by 0.001, 0.010, and 0.100, the changes in predicted utility are -0.077, -0.770, and -7.197, respectively, which demonstrates a linear relationship between cost and utility.

Although the proposed model can achieve high predicting accuracy on comparisons for shipper preferences (93%), it is important to note that the ability to predict the value of utility can be related to the preference distribution within classes and the range of training datasets.

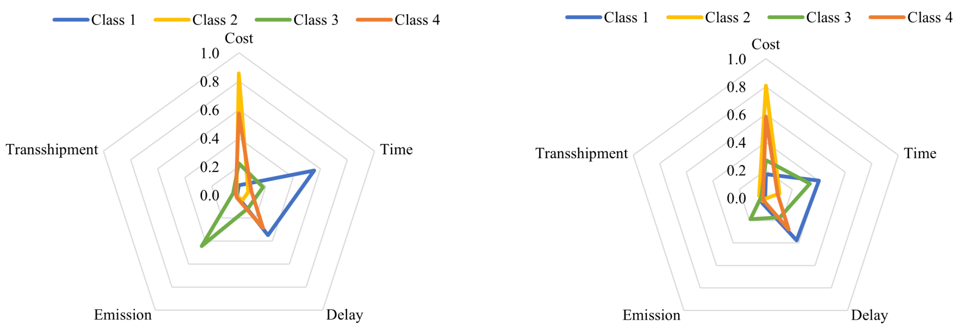
The impacts of transport attributes, that are prioritized and have a greater impact on utility, are easier to capture than non-prioritized attributes. As shown in Table 4.7, NN-PMs are able to accurately predict the preferences of Class 2 for transport time and delay, but have limited ability to predict the impact of emissions. In addition, it is easier to capture the preferences with a higher level of prioritization (Class 1 and Class 2) than those without clear preferences (Class 3 and Class 4). For example, for Class 3, the changes in cost are relatively large considering the true preference of this class (sensitive to emission). This finding is in line with the results shown in Figure 4.7. This may be due to the models being trained using comparisons, which may result in information loss regarding the exact values of utilities for non-prioritized attributes.

Based on the utility changes with the variation of 0.01, Figure 4.9a and Figure 4.9b show the relative importance of transport attributes in true preferences and predicted preferences, respectively. It shows that, in comparison to the true relative importance, the learned preference pattern by NN-PMs can differentiate between shipper classes, which is a key factor in the outperformance of NN-PMs over NNs and BLs in heterogeneous scenarios. However, it is important to note that there is still space for improvement in fully recovering the degree of attribute prioritization in classes. As shown in Figure 4.9, the actual sensitivity of shippers in Class 1 and Class 3 to transport cost and emission, respectively, should be greater than their predicted preferences.

Table 4.7: The utility changes of NN-PMs with the attribute variances

	0.001	0.010	0.100	Sensitivity
Cost				
Class 1	-0.077	-0.770	-7.197	*
Class 2	-0.283	-2.832	-28.351	****
Class 3	-0.110	-1.021	-12.104	**
Class 4	-0.259	-2.574	-25.875	***
Time				
Class 1	-0.181	-1.805	-21.605	****
Class 2	-0.037	-0.368	-3.683	*
Class 3	-0.125	-1.251	-10.471	***
Class 4	-0.039	-0.393	-3.934	**
Delay				
Class 1	-0.169	-1.691	-16.775	****
Class 2	0.001	0.014	0.141	*
Class 3	-0.065	-0.649	-6.146	**
Class 4	-0.123	-1.231	-12.310	***
Emission				
Class 1	0.020	0.204	2.041	*
Class 2	0.011	0.112	1.296	**
Class 3	-0.071	-0.709	-7.080	****
Class 4	-0.011	-0.112	-1.114	***
Transshipment				
Class 1	-0.004	-0.025	-0.158	*
Class 2	0.010	0.179	2.045	**
Class 3	-0.013	-0.127	-1.291	****
Class 4	0.010	0.096	0.964	***

Note.**** means the class is the most sensitive class for a specific attribute.



(a) True classes

(b) Learned classes

Figure 4.9: The relative importance of attributes

4.3 Experiments on synchromodal transport planning

This section examines the performance of the synchromodal transport planning model with shippers' preference learning (STPM-SP). The trained utility estimators are utilized during the planning process to assess the satisfaction level of shippers towards transport solutions. The synchromodal transport planning model (STPM) is used as a benchmark model to compare the impact of integrating preference information on transport solutions. To examine this effect, we conduct experiments in four scenarios (HoS1, HoS2, HeS1, HeS2) using synchromodal transport planning modals (STPM, STPM-SP).

4.3.1 Synchromodal transport planning with shippers' preferences

In total, there are 80 instances of synchromodal transport operations conducted by running five instances for each combination of scenarios, models, and request numbers, as shown in Table 4.8. Table 4.9 presented the computational time of STPM and STPM-SP.

Table 4.8: The experiment settings

Settings	
Scenario	[HoS1, HoS2, HeS1, HeS2]
Models	[STPM (baseline), STPM-SP]
Number of requests	[10,50,100,150]
Repetition	5

Table 4.9: The computational time of STPM and STPM-SP (unit: hour)

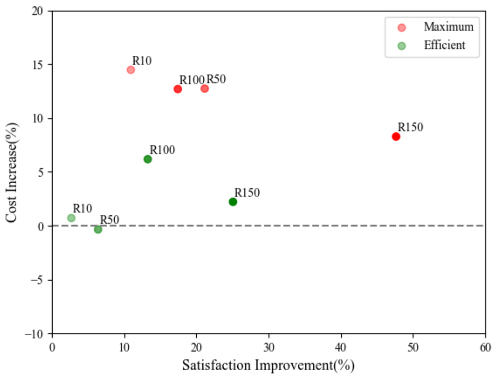
Request	STPM	STPM-SP
10	0.06	0.08
50	1.81	2.02
100	9.92	9.85
150	26.29	23.41

Figure 4.10 presents the satisfaction improvement and the corresponding cost increase in the experiments. The red dots represent the average values of maximum satisfaction improvement and the corresponding cost increase within Pareto sets of five instances of synchromodal transport planning. The green dots represent the average values of satisfaction improvement and cost increase for the most efficient trade-offs, determined by the ratio of the gap between satisfaction improvement and cost increase to satisfaction improvement. Each label along the dots indicates the number of requests in a single instance, with 'R100' indicating 100 requests. The specific values for these experiments are shown in Table 4.10

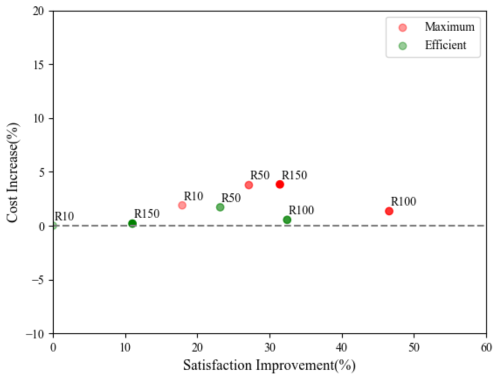
By comparing the solutions with the most satisfaction improvement (in red) and the solutions with the most cost-efficient satisfaction improvement (in green), it can be observed that the most efficient satisfaction tends to be approximately half of the maximum satisfaction attained. However, there can be certain combinations where it is challenging to find cost-efficient trade-offs, resulting in relatively low improvements in efficiency. For example, the cost-efficient satisfaction improvement for instances of R10 in HoS1 (Figure 4.10a) and HoS2 (Figure 4.10b) are relatively low.

In the scenarios where all shippers share the same preference, the trade-offs between cost and shippers' satisfaction appear to be less cost-efficient compared to the scenarios with heterogeneous preferences. It is observed that in HeS1 (Figure 4.10c), instances with a request size of 10, 50, and 100 tend to have higher satisfaction levels with a relatively smaller increase in cost. For example, in the R100 case of HoS1 (Figure 4.10a), the average maximum satisfaction improvement is approximately 17.44%, whereas, in HeS1 (Figure 4.10c), where there are four classes of shippers with different preferences, the value can be increased to 25.53% with a lower increase in cost (8.03%). In the case of 150 requests, although HoS1 shows a larger satisfaction improvement (47.67%), HeS1, with the most efficient solution proposed by STPM-SP, can provide win-win solutions, that is, satisfaction improved by 9.28% while simultaneously reducing costs by 1.04%. This can be explained by the fact that when shippers' preferences differ, freight forwarders have the flexibility to reallocate resources that have already been utilized, adjusting the allocation across shippers instead of requiring additional resources for satisfaction improvement.

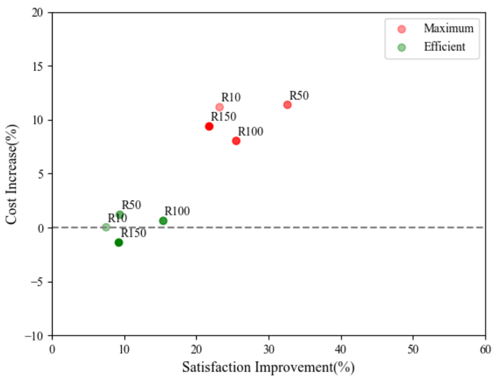
By comparing the outcomes of different true model specifications, a notable trend is that the satisfaction improvement is more significant in the nonlinear cases (Figure 4.10b 4.10d) compared to the linear cases (Figure 4.10a 4.10c). This could be attributed to the fact that the attribute changes in the nonlinear functions used in this research have a greater impact on satisfaction compared to the changes in linear functions. Therefore, the extent to the satisfaction can be improved is closely related to the relationship between true utility and the factors influencing it. Nonlinear functions may amplify the effects of attribute changes, leading to more substantial improvements in satisfaction.



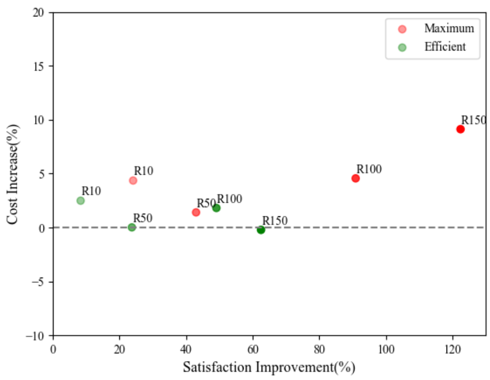
(a) HoS1



(b) HoS2



(c) HeS1



(d) HeS2

Figure 4.10: The changes in the satisfaction improvement and cost increase in the scenarios

Table 4.10: The numerical results of satisfaction improvement and cost increase

	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%

Notes: 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 efficient satisfaction

4.3.2 Synchromodal transport planning with homogeneous preferences

Figure 4.11 compares the solution attributes between the solution proposed by STPM (base solution) and the Pareto solution set with 6 non-dominated solutions of STPM-SP on the same 100 requests. Taking the best solution proposed by STPM as the base solution, the variations of solution attributes in the Pareto set are shown.

The Pareto set of non-dominated solutions has a satisfaction improvement ranging from 18.72% to 26.98%. It appears that all of these non-dominated solutions have higher generalized costs, costs, and emissions compared to the base solution. However, they also require shorter times, suggesting that shippers prioritize faster delivery over lower costs and emissions. Solution 1 has the largest satisfaction improvement (26.98%) among the non-dominated solutions in the Pareto set. However, it also has the most significant increase in generalized cost, cost, and emissions compared to the base solution. In addition, trade-offs between different solution attributes can be observed, for example, S2 and S1 have similar satisfaction, but S2 has less increase in cost and emissions compared to S1, and it reduces time and transshipment. However, such improvement is based on the trade-off of the increase in delay. The specific values are listed in Table C.3 in Appendix.

To better understand the influence of STPM-SP on the individual shipper, the individual satisfaction improvement and modal share are investigated for solution 78, which achieves the highest satisfaction improvement among all the Pareto solutions proposed by STPM-SP.

Figure 4.12 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 improves the satisfaction levels of the shipper compared to the solution generated by the STPM model, otherwise, the value is negative shown in blue. Figure 4.12 shows performance variability for shippers. 71.9% shippers have increased satisfaction while 28.1% satisfactions ex-

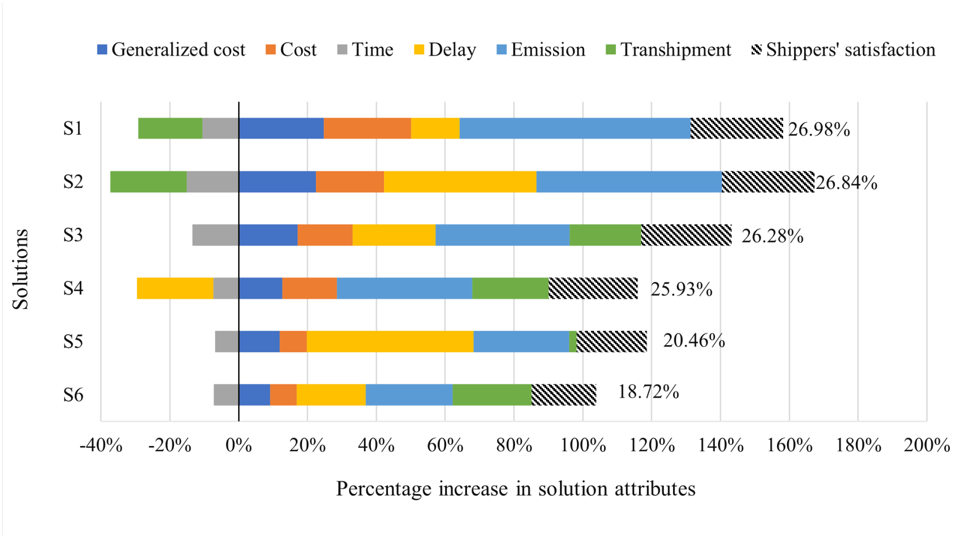


Figure 4.11: The comparison between the base solution and the Pareto solutions in HoS1

perience setbacks. 65.7% of the shippers have experienced a satisfaction increase of less than 50%, while 6.2% of shippers have a satisfaction decrease of more than 100%.

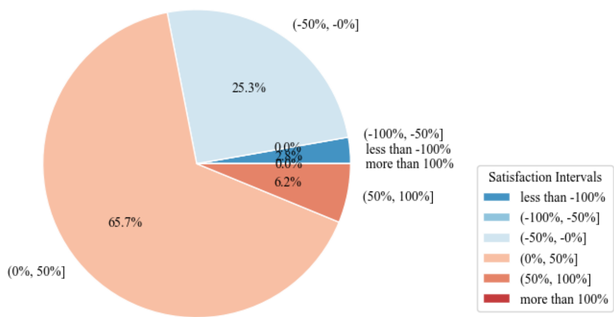


Figure 4.12: Proportions of shippers based on satisfaction improvement

Figure 4.13 shows the average changes in modal share between the STPM solutions and the STPM-SP solutions in the instances with 100 requests, and Table 4.11 shows the percentages of trips by mode shift. In general, the barge mode accounts for the largest proportion of trips in both the STPM solutions and the STPM-SP solutions, with shares of 58.64% and 57.64% respectively. Most of the barge, train and truck trips in the base solution (55.756%, 9.375% and 28.696%) remain using their original mode, with only a small proportion of trips shifting to other modes.

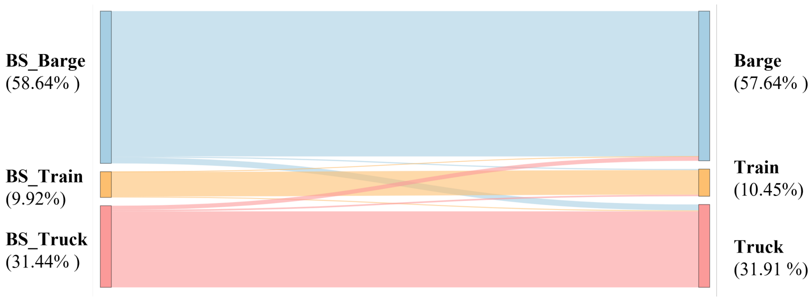


Figure 4.13: The shift of modal share between the STPM solution and the STPM-SP solution

Table 4.11: Percentages of trips in modal shift

From-To	Percentage of trips
Barge-Barge	55.756%
Barge-Train	0.195%
Barge-Truck	2.687%
Train-Barge	0.120%
Train-Train	9.375%
Train-Truck	0.422%
Truck-Barge	2.236%
Truck-Train	0.509%
Truck-Truck	28.696%

4.3.3 Synchromodal transport planning with heterogeneous preferences

Figure 4.14 shows the comparison between the base solution generated by STPM and the Pareto solution proposed by STPM-SP. Among the Pareto solutions, S1 demonstrates the greatest improvement in shippers' satisfaction, with an increase of 23.46%, followed by S2. The main reason for such improvement is the reduction of delay, transport time, and transport cost, although it comes at the expense of higher emissions. Another solution, S6, also exhibits significant reductions in delay and transport costs while requiring longer time and transshipment. The specific values are listed in Table C.4 in Appendix.

Figure 4.15 illustrates the average distribution of shippers based on their satisfaction improvement in instances with 100 requests. It is observed that a majority of shippers (68.3%) experience a higher level of service, with 59.6% of the improvement falling within the range of $[0\%, 50\%)$. A few shippers experience a reduction in satisfaction of more than 100%. Therefore, in practice, it is crucial to investigate the underlying reasons and take measures to prevent significant decreases in satisfaction for these shippers. Figure 4.16 shows the average modal share changes between the base solution (the optimal solution proposed by STPM) and the Pareto solution with maximize satisfaction proposed by STPM-SP. Table 4.12 shows specific numerical values of modal share shift. Overall, the changes in mode share are not particularly significant, with a slight increase of 0.16% in train share, 0.37% in truck share, and marginal decreases of 0.53% in barge share.

Figure 4.17 shows the distribution of improvements across shipper classes. Among shippers in class 3, 80% experienced an improvement in satisfaction. The values are 67.39% and 76.19% for class 1 and class 2, respectively. However, in class 4, which prioritizes cost and delay, only 42.85% of shippers have satisfaction improvement. This indicates that compared to other classes, the satisfaction of class 4 is more challenging to improve. This could be because the trade-off between cost and delay is significantly stronger, making it more difficult to achieve improvements by adjusting transport plans.

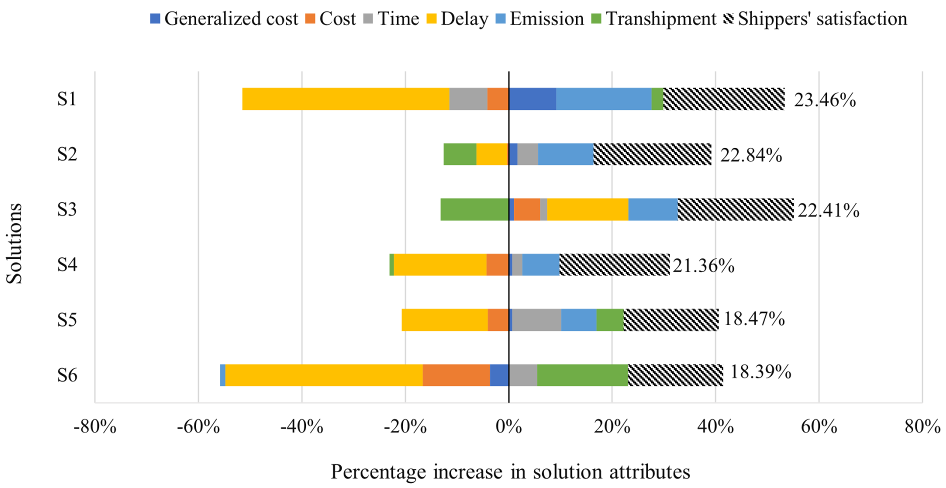


Figure 4.14: The comparison between the base solution and the Pareto solutions in HeS1

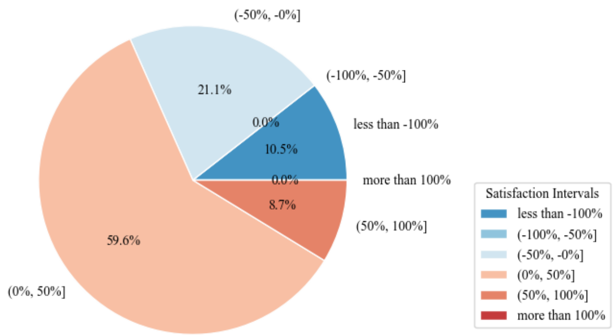


Figure 4.15: Proportions of shippers based on satisfaction improvement

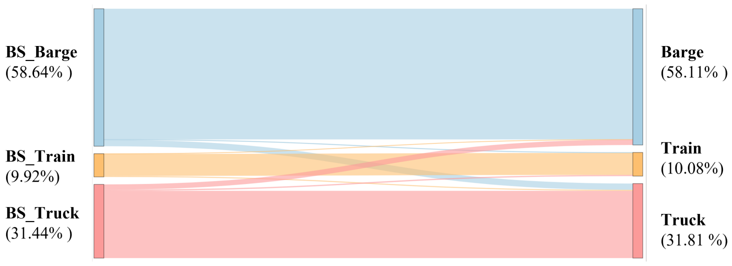


Figure 4.16: The shift of modal share between the base solution and the STPM-SP solution

Table 4.12: Percentages of trips in modal shift

From-To	Percentage of trips
Barge-Barge	55.756%
Barge-Train	0.195%
Barge-Truck	2.687%
Train-Barge	0.120%
Train-Train	9.375%
Train-Truck	0.422%
Truck-Barge	2.236%
Truck-Train	0.509%
Truck-Truck	28.696%

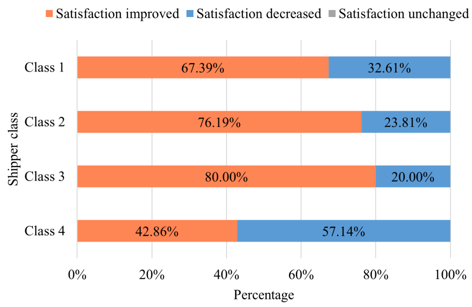


Figure 4.17: Proportions of shippers with satisfaction changes in classes

Figure 4.18 presents the transport attribute for each class of shippers and Table 4.13 presents the corresponding values of changes. Specifically, the percentages represent the extent of increase or decrease in the transport attribute, compared to the optimal solution generated by STPM. After the incorporation of heterogeneous preferences, shippers in class 1, who prioritize time and delay, have a decrease in average emission, delay, and cost, while transshipment and time increased. It is noted that although both time and delay are prioritized in class 1 according to the true preferences, the average delay reduces by 23.95%, while time increases by 10.57%. This finding highlights the ability of STPM-SP to not only identify the prioritized attributes but also effectively capture the trade-offs between these attributes and search for the most enhancements in satisfaction. The shippers in classes 1, 2, and 3 experience significant changes in transshipments, with percentages of 104.76%, -41.44%, and -48.89%, respectively. This underscores the importance of transshipment in synchromodal transport operations, as it enhances flexibility and offers more opportunities for the adjustments of resource allocation among different classes of shippers.

According to Figure 4.17, class 3 has the highest proportion of shippers with improved satisfaction. Although the average emission for class 3 requests only decreased by 1.17% (the most prioritized attribute in class 1), the decrease in time by 20.58% becomes the contributing factor for this improvement. Therefore, it is crucial to have a comprehensive understanding of shippers' preferences rather than relying on partial knowledge. This is because there may be scenarios where improving attributes that are not the most prioritized can still result in increased satisfaction for shippers.

When looking into the Pareto solution, Figure 4.19 compares the modal share across different shipper classes. It is observed that class 1 and class 2 have a significant proportion of barge usage, accounting for 59.14% and 64.54% respectively. The truck share of class 1 is larger than that of class 2, indicating their distinct preferences, which is that class 1 prioritizes short transport time and low delay, while class 2 values cost-effectiveness. Regarding class 3, truck trips account for a relatively high proportion (40.00%). This aligns with the finding from Figure 4.18, which indicates that the satisfaction improvement for class 3 is primarily driven by time reduction rather than

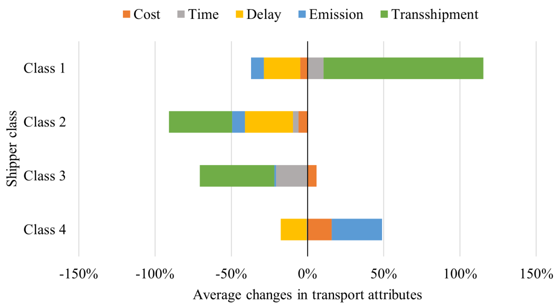


Figure 4.18: Comparison of transport attributes for shippers

Table 4.13: The comparison of transport attributes for shippers

Comparison	Cost	Time	Delay	Emission	Transshipment
Class 1	-4.73%	10.57%	-23.95%	-8.44%	104.76%
Class 2	-6.01%	-3.54%	-31.55%	-8.41%	-41.44%
Class 3	5.98%	-20.58%	0.00%	-1.17%	-48.89%
Class 4	15.88%	-0.61%	-16.97%	32.98%	0.00%

the prioritized attribute of emission reduction. For class 4, who prioritize both cost and delay, the train can be a suitable option since they offer a balance between lower cost compared to trucks and faster travel times compared to barges. This finding highlights the benefits of multimodal transportation over single-mode transportation. Through the integration of multiple modes of transport, multimodal solutions can effectively leverage the strengths of different modes and be adjusted to fulfill the specific preferences of diverse shippers.

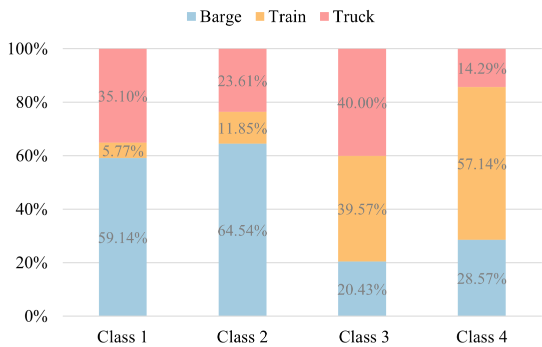


Figure 4.19: The modal share in the S1 across shipper classes

Chapter 5

Discussions

This section presents the discussions and reflections on the research methodology and experimental results.

5.1 Discussions on the methodology framework

The research aims to develop a foundational framework for a shipper-oriented synchromodal transport system, integrating synchromodal transport planning with shippers' preference learning. This framework can enable freight forwarders to offer customized transport solutions and improve the attractiveness of transport services, which will enhance existing business relationships and facilitate the expansion of the customer base.

The traditional methods for studying shippers' preferences are commonly based on 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 biases and challenges associated with large-scale data collection. The hypothetical nature of survey may lead to responses that do not accurately reflect shippers' true preferences in practical situations. Based on these considerations, this research aims to utilize revealed preference data and the basic idea is to utilize the data generated from the transport system to improve the system itself. In this approach, when shippers have transport requests, they are presented with multiple alternative transport plans and are requested to rank these provided options. Unlike the traditional method that relies on hypothetical ratings, this ranking method captures shippers' preferences in their actual decision-making process, resulting in a more accurate reflection of their preferences. As the transport system serves shippers over time, the preference database can expand, allowing for a more extensive and robust understanding of shippers' preferences.

The motivation behind incorporating artificial neural network-based preference learning into synchromodal transport planning stems from its ability to leverage large-scale revealed preference data and autonomously capture preferences without prior knowledge of variable relationships. This approach holds potential for online operation, enabling the identification of preferences for new shippers.

To implement the proposed framework in practice, several aspects need to be considered. Firstly, the feedback collection requires an advanced data storage system and management system to accommodate the storage and retrieval of significant amounts of data, including information such as shippers' IDs, their rankings of transport plans and transport attributes of alternative plans. Second, active collaboration from shippers is essential for the success of this approach. Shippers would be required to provide their feedback on the provided transport plans and understand that the top-ranked plan may not always be implemented (as the freight forwarders are the final decision maker of this system). Furthermore, freight forwarders are required to invest additional efforts in presenting candidate solutions for each shipper and have appropriate measures for shippers' privacy protection.

5.2 Discussions on the preference learning

Considering the flexibility and scalability, this research uses synthetic preference data for model evaluation. synthetic data can simulate "what if" scenarios of shippers' preferences, allowing this research to test the capacity of the proposed models under various conditions (i.e., homogeneity, heterogeneity, linearity, nonlinearity). Synthetic data can provide sufficient samples for model testing and examine the performance of the proposed models at different scales of dataset. For this research, the collection of feedback data during the actual transport process can be challenging, considering the duration of transport operations, shippers' privacy, and business confidentiality.

This research uses binary logit models as the baseline model in preference learning and compares them with artificial neural networks. The purpose of this comparison is to explore how each model adapts under different conditions and gain insights into the reasons for their respective performance, rather than to determine a definitive superior model. The model comparison enables a better understanding of the fundamental characteristics between statistical-based utility estimators and data-driven utility estimators. The former one incorporates prior knowledge and relies on a smaller number of parameters, and the other releases model specifications but requires an expanded parameter space. It should be noted that the discussion on both baseline models and proposed models is restricted to the specific model settings, in which the binary logit models have a linear combination of attributes and artificial neural networks are five-layer feedforward networks with the ReLU activation function.

As the binary logit model is a basic form of the discrete choice model, it cannot fully represent the capabilities of the entire discrete choice model family. This research suggests it is worthwhile to investigate more advanced discrete choice models. For example, Box–Cox transforms [38] or logarithms [39] can be integrated into the model specification for modeling nonlinearity. The latent class discrete choice model can analyze preference heterogeneity by estimating the probability of individuals belonging to specific classes and class-specific probabilities [37, 19]. It is important to note that discrete choice models require prior statistical experiments to ensure the chosen model can accurately represent the underlying preferences. When selecting the appropriate model specification, researchers should have careful consideration of the relationships between the variables and the utilities, including non-linear transformations of variables and interactions between them. In comparison, the neural network structure may provide opportunities to simplify the preparation work for model specification, enhance prediction accuracy, and reduce the risk of inappropriate specification. Furthermore, artificial neural networks may adapt to new data and identify patterns that cannot be easily discerned using conventional statistical methods.

5.3 Discussions on the results

The experiments present two trade-offs related to model selection in preference learning. The first trade-off is that although artificial neural networks release the prior assumptions regarding variable relationships, this advantage comes at the cost of requiring large-scale training data and parameters, which can place a significant workload on data collection and hyperparameter tuning. The second trade-off relates to the model's capacity for generalization and explanations. Artificial neural networks employ a large number of parameters, relax the assumptions regarding the model specification and enable generalization of the model structure. Nonetheless, the increased complexity resulting from parameters makes it challenging to provide clear explanations for shippers' behavior. This research applies SHAP for model explanation for the homogeneous preference scenario, while it cannot analyze the potential interactive effect between variables (i.e., the preference matrix and transport attributes) and is still limited to explain the heterogenous preferences.

For the experiments of transport planning, this research chooses the STPM model as the baseline to conduct a comparative evaluation with the proposed STPM-SP model. The primary task of experiments is to integrate preference information into the planning process and quantify the extent to which satisfaction can be enhanced. Additionally, this research explores various aspects such as the trade-off within different Pareto solutions, the distribution of satisfaction improvement among shippers, and the changes in model shares. Results show that the proposed STPM-SP can improve the shippers' satisfaction by 37% on average compared to the solution that resulted in STPM. Results also demonstrate the importance of a comprehensive understanding of shippers' preferences because it can be possible that the enhanced attributes may not be the highest prioritized ones but can still result in increased satisfaction for shippers. Furthermore, the incorporation of shippers' preference has the potential to effectively increase the modal share of sustainable modes while simultaneously improving shippers' satisfaction. By aligning the preferences of shippers with the environmental goals, freight forwarders can have win-win solutions for future synchromodal transport planning.

Chapter 6

Conclusions and Recommendations

This chapter presents the main conclusions and discusses future research directions.

6.1 Conclusions

This study develops a foundational framework for integrating synchromodal transport planning and preference learning. An artificial neural network-based preference learning method is proposed to capture the preference information from shippers' feedback data in transport operations. A synchromodal transport planning model with shippers' preferences (STPM-SP) is proposed to support the decision-making of freight forwarders incorporating shippers' preferences. The model considers two objectives minimizing the total cost and maximizing shippers' satisfaction. The Adaptive Large Neighborhood Search is modified to solve the STPM-SP.

The proposed preference learning method can effectively capture both linear and nonlinear relationships between variables and utilities using large-scale datasets, without the prior model specification. It can also automatically distinguish the heterogeneity of preferences with the information of historical decisions. In comparison to statistical-based discrete choice models, the structure of artificial neural networks has the potential to simplify the preparatory work required for model specification, reducing the risk of inappropriate specification.

The planning results demonstrate that STPM-SP can effectively find solutions with a significant satisfaction improvement of about 37%. The distribution of shippers' satisfaction indicates that achieving satisfaction improvement can not only be related to the allocation of extra resources but also involves the trade-off between the resources assigned to shippers. STPM-SP can optimize this trade-off to maximize overall satisfaction. Furthermore, the results also present the importance of a comprehensive understanding of shippers' preferences since it can be possible that the enhanced attributes may not be the highest prioritized ones in preferences but can still result in a significant satisfaction increase for shippers.

The proposed framework can serve as the foundation for the user-oriented synchromodal transport services that freight forwarders can learn from shippers' preferences from revealed preference data collected in the system and improve their services accordingly. As the transport system serves shippers over time, the preference database can expand, allowing for a more extensive and robust understanding of shippers' preferences. This process can be iterative and has the potential for online learning and continual improvement of the system, building the capacity of freight forwarders to provide transport plans that align with the preferences of new shippers and adapt to the evolving preferences of existing shippers.

Based on the discussion, the answers to the research questions can be concluded as follows:

RQ 1: How to learn shippers' preferences from their rankings on alternatives of transport plans?

When shippers have transport requests, they are presented with multiple alternative transport plans and are requested to rank these provided options. An artificial neural network-based preference learning method is proposed to capture the preference information from shippers' feedback data in transport operations.

RQ 2: To what extent the true preferences can be captured from the ranking data?

The proposed preference learning method can effectively capture both linear and nonlinear relationships between variables and utilities using a large-scale dataset with a prediction accuracy above 85% in four tested scenarios, without the prior model specification. It can also automatically distinguish the heterogeneity of preferences based on the information on historical decisions.

RQ 3: How to incorporate preferences into synchromodal transport planning?

A sychromodal transport planning model with shippers' preferences (STPM-SP) is proposed to support the decision making of freight forwarders incorporating with shippers' preferences. The model considers two objectives of minimizing the total cost and maximizing shippers' satisfaction. The output of the preference learning method is used as a utility estimator to calculate the shippers' satisfaction.

RQ 4: To what extent the transport services can be improved according to the learned preferences?

The planning results demonstrate that STPM-SP can effectively find solutions with a significant satisfaction improvement of about 37%. The most cost-efficient satisfaction improvement tends to be approximately half of the maximum satisfaction attained.

6.2 Practical recommendations

Based on the findings, this thesis can provide several recommendations for practice for transportation service providers and policy-makers, which are listed as follows:

- A better understanding of shippers' preferences can help freight forwarders to identify gaps between the current service level and shippers' expectations, which enables them to recognize the areas in which their services may not fully meet the expectations of shippers. There may be scenarios where improving attributes that are not the most prioritized can still result in increased satisfaction for shippers.
- The integrated framework of synchromodal transport planning and preference learning can also be used in single-mode or intermodal transport systems. It can be more valuable for synchromodal transport planning with real-time information updates, as the system requires making prompt decisions from freight forwarders during transport operations to accommodate real-time modifications. Instead of consulting shippers for plan adjustments frequently, freight forwarders can leverage their knowledge of shippers' preferences to make quicker and more informed decisions.
- For discrete choice models, statistical experiments and analyses are required to determine the appropriate model specification. Incorrect model specifications can lead to undesired performance outcomes. Artificial neural networks can autonomously capture nonlinear relationships between variables rather than relying on strong model specifications. While the potential trade-offs also should be noted, including the explanation capability, hyperparameter tuning, and the requirement for a large sample size.

6.3 Limitations and future research

Based on the conclusions, this research reflects the limitations and proposes several suggestions for future research:

- This research simulates the shippers' ranking on transport plans based on the predefined utility functions. However, synthetic data may not capture the full range of factors and complexity that exist in real-world scenarios. Therefore, it is crucial to incorporate the actual shipper ranking data in future research, which will provide a more comprehensive and realistic understanding of real shippers' preferences and better demonstrate the applicability and effectiveness of the models.

- This research examines the predictive capabilities of binary logit models and artificial neural networks in preference learning. It can be argued that the binary logit model is a basic form of discrete choice model and may not fully represent the capabilities of the entire discrete choice model family. In future research, more advanced model structures can be explored. For instance, within the family of discrete choice models, latent class models are designed for heterogeneous preferences, and mixed logit models allow for the exploration of individual preferences. For artificial neural networks, the predictive power may be enhanced by incorporating self-attention mechanisms and recurrence structures.

- In the experiments for synchromodal transport planning, the selection of variables and parameters presented serves as an illustrative list that represents general shipper preferences. It is important to note that this list may not be comprehensive. Future studies may explore a wider range of variables to incorporate into the modeling process, and this research suggests that some potential variables that could be considered include shippers' characteristics, company types, and cargo types.

- In STPM-SP, shippers' satisfaction with the transport solution is quantified by summing the satisfaction of all shippers. However, in practical operations, freight forwarders often assign priority to shippers based on their business relationships. Future optimization models can take this into account by assigning different weights to individual shippers or incorporating specific enhancements for certain shippers as constraints. This would better reflect real-world transport operations and improve the practicability of the optimization models.

- This research focuses on learning shippers' preferences based on historical data. The new challenge lies in capturing the preferences of new shippers. It remains uncertain whether the preferences of new shippers can be learned, especially if they differ from the preferences of existing shippers. Furthermore, it is unclear how long it takes, or after how many services, such preferences can be accurately predicted. It is worthwhile to investigate the feasibility and efficiency of the proposed models in capturing the preferences of new shippers and incorporate such information into the online planning process.

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Appendix A

Summary

A.1 Summary

A comprehensive understanding of shippers' preferences can empower transport freight forwarders to provide user-oriented transport services and strengthen long-term business relationships. In synchromodal transport research field, many studies addressed the transport planning problem from the perspective of freight forwarders, while the considerations of shippers can be diverse from freight forwarders. There is still a lack of insight into incorporating the benefit of shippers into the transport planning and it is unclear how to leverage the potential of customer data to improve services. To this end, this thesis develops a foundational framework for integrating synchromodal transport planning and preference learning to capture shippers' preference in the transport process and enable freight forwarders to make more informed decisions. This framework can serve as the foundation for the user-oriented synchromodal transport services that freight forwarders provide services while simultaneously learning from shippers' preferences. It emphasizes the data collection within the transport system and improves services based on the preferences of shippers.

To integrate synchromodal transport planning and preference learning, there are two major research problems: the shippers' preference learning problem and the bi-objective synchromodal transport planning problem. A preference learning model is proposed, which utilizes shippers' decisions on transport services to estimate their preferences. Artificial neural networks are used to approximate shippers' satisfaction with transport services. A synchromodal transport planning model considering shippers' preferences is established using a heuristic algorithm. In this approach, when shippers have transport requests, they are presented with multiple alternative transport plans and are requested to rank these provided options. This ranking method captures shippers' preferences in their actual decision-making process, resulting in an accurate reflection of their preferences. As the transport system serves shippers over time, the preference database can expand, allowing for a more extensive and robust understanding of shippers' preferences. Considering the characteristics of shippers' real preferences, four 'what if' scenarios are designed: homogeneous linear preference scenario (HoS1), homogeneous nonlinear preference scenario (HoS2), heterogenous linear preference scenario (HeS1), and heterogenous nonlinear preference scenario (HeS2).

A.1.1 Summary on the preference learning

The experiments on preference learning examined the performance of binary logit models (BLs), artificial neural networks (NNs), and artificial neural networks with preference matrix as input (NN-PMs). The performances of the models are evaluated based on prediction accuracy and log loss. Results show that the increase in sample size can generally decrease prediction errors, and artificial neural networks are particularly sensitive to changes in sample size. In scenarios with homogeneous preferences, both BLs, and NNs have a high accuracy in HoS1. BLs can efficiently capture shippers' preferences when the structures of model specification and the real preferences are the same. Considering Scenario HoS2, NNs significantly outperform BLs implying that the structure of NNs can be effective in capturing the nonlinearity in preference datasets without the prior knowledge on real preferences. In scenarios with heterogeneous preferences, NN-PMs outperform BLs and NNs in terms of both accuracy and log loss. This can be because the architecture of artificial neural networks is capable of modeling heterogeneity through the incorporation of the preference matrix. For model explanation, SHAP is applied to explain individual preference in homogenous scenarios. This research discussed the contributions of each transport attribute (i.e., cost, time, delay, emission, transshipment) to the predicted utilities, taking the base utility value as the basis point. The predicted utilities of the two alternatives are investigated and the differences are analyzed. For the heterogeneous cases, this research investigated the influences of attribute variances on utilities. It is found that the impacts of transport attributes, that are prioritized and have a greater impact on utility, are easier to capture than non-prioritized attributes.

A.1.2 Summary on the synchrmodal transport planning

The analysis of satisfaction improvement and cost increase in the Pareto solutions of STPM-SP demonstrates the effectiveness of STPM-SP in finding solutions with significant satisfaction improvement. The extent of improvement and trade-offs with cost was found to be influenced by preference scenarios, the relationship between influential attributes and utility, and the number of requests. The proposed STPM-SP can improve the shippers' satisfaction by 37% on average compared to the solution that resulted in STPM.

While STPM-SP effectively improves overall satisfaction, it is important to examine how these benefits are distributed among shippers in individual instances. In both the homogeneous and heterogeneous cases, it is observed that while some shippers experience increased satisfaction, others face setbacks. It is crucial to note that achieving satisfaction improvement is not only related to the allocation of extra resources but also involves the trade-off between shippers' satisfaction and resource utilization between shippers. STPM-SP was able to optimize this trade-off to maximize overall satisfaction. In practice, there might be a need to balance or equalize the improvements across shippers, or sometimes to prioritize specific shippers. STPM-SP can adapt to these situations by incorporating these additional constraints.

Based on the analysis of modal share, this research also demonstrates the potential for increasing the modal shares of sustainable modes through improvements in critical attributes for shippers, such as time, emission, and transshipment of the transport system. Given the current emphasis on environmental sustainability, freight forwarders can explore opportunities to enhance specific attributes that are important to shippers. By doing so, they can effectively increase the modal share of sustainable modes while simultaneously improving shippers' satisfaction. By aligning the preferences of shippers with the environmental goals, freight forwarders can have win-win solutions for future synchromodal transport planning.

When analyzing the scenarios of heterogeneous preferences, it shows that the improvement in satisfaction may not be attributed to advancements in the prioritized attributes. For instance, while the average emission for class 3 requests (the most prioritized attribute in class 3) only decreased by 1.17%, the significant reduction in time by 20.58% becomes a contributing factor to the overall improvement. This observation emphasizes the importance of understanding shippers' preferences comprehensively because it can be possible to identify scenarios where the enhanced attributes may not be the highest prioritized ones but can still result in increased satisfaction for shippers.

Appendix B

Supplementary results for preference learning

This appendix is the supplementary results for the experiments of preference learning.

B.1 Relative importance of transport attributes

Table B.1 lists the relative importance of transport attributes for different classes of shippers in the real preferences, and Table B.2 shows the values of preference learning using NN-PMs.

Table B.1: Relative importance of transport attributes in true preferences

	Cost	Time	Delay	Emission	Transshipment
Class 1	6.94%	55.56%	34.72%	1.39%	1.39%
Class 2	85.47%	6.84%	4.27%	1.71%	1.71%
Class 3	22.22%	17.78%	11.11%	44.44%	4.44%
Class 4	57.47%	9.20%	28.74%	2.30%	2.30%

Table B.2: Relative importance of transport attributes in captured preferences

	Cost	Time	Delay	Emission	Transshipment
Class 1	17.12%	40.17%	37.61%	4.54%	0.56%
Class 2	63.01%	8.19%	0.32%	2.50%	3.98%
Class 3	22.72%	27.83%	14.44%	15.78%	2.83%
Class 4	57.28%	8.75%	27.39%	2.50%	2.14%

B.2 Prediction performance across shipper classes

Table B.3 presents the prediction performance of NN-PMs across shipper classes. p(c) is the percentage of correctly predicted tested samples, and p(c) is the percentage of incorrectly predicted tested samples. The visualization of this table is shown in Figure 4.7.

Table B.3: Prediction results of different classes in HoS1

	Class 1		Class 2		Class 3		Class 4		Total
	p(c)	p(i)	p(c)	p(i)	p(c)	p(i)	p(c)	p(i)	
HeS1									
BL	28.44%	6.14%	42.30%	1.30%	10.88%	3.48%	6.52%	0.94%	100.00%
NN	28.66%	5.92%	41.40%	0.92%	11.26%	4.38%	6.60%	0.86%	100.00%
NN-PM	33.74%	0.84%	45.38%	1.38%	10.80%	0.26%	7.20%	0.40%	100.00%
HeS2									
BL	17.62%	16.96%	24.62%	21.16%	5.26%	6.92%	2.84%	4.62%	100.00%
NN	25.62%	8.96%	36.22%	9.56%	9.26%	2.92%	6.26%	1.20%	100.00%
NN-PM	27.74%	6.84%	40.90%	1.72%	10.46%	4.88%	6.12%	1.34%	100.00%

Appendix C

Supplementary results for synchromodal transport planning

C.1 Parameters of STPM-SP

The parameters in STPM-SP are shown in Table C.1

Table C.1: Parameter settings in the synchromodal transport planning model

Parameter	Value	Parameter	Value	Parameter	Value
c^t_{truck}	0.2758	c^t_{train}	0.0635	c^t_{barge}	0.0213
c^l_{truck}	3	c^l_{train}	18	c^l_{barge}	18
c^s_k	1	c^w_k	1	c^e_k	4
e_{truck}	0.8866	e_{train}	0.3146	e_{barge}	0.2288

C.2 Overview of scenario comparison

Table C.2 presents the satisfaction improvements and corresponding cost increases in solutions of STPM-PL compared to STPM. The column 'SI_max' means the average of maximum satisfaction improvements in the Pareto sets and 'CI_max' is the corresponding cost increases. The negative values suggest a cost reduction. The column 'SI_eff' means the average of the most effective satisfaction improvements and 'CI_eff' is the corresponding cost increases. The effectiveness focuses on the trade-offs between satisfaction and cost.

Table C.2: The comparison of solutions of STMP and STPM-SP

Scenario	HoS1			
	SI_max	CI_max	SI_eff	CI_eff
R10	10.94%	14.48%	2.70%	0.71%
R50	21.17%	12.73%	6.40%	-0.35%
R100	17.44%	12.69%	13.28%	6.18%
R150	47.67%	8.28%	25.09%	2.22%
Scenario	HoS2			
	SI_max	CI_max	SI_eff	CI_eff
R10	17.91%	1.89%	0.02%	0.00%
R50	27.14%	3.77%	23.18%	1.71%
R100	46.57%	1.35%	32.45%	0.54%
R150	31.44%	3.84%	11.02%	0.20%
Scenario	HeS1			
	SI_max	CI_max	SI_eff	CI_eff
R10	23.23%	11.16%	7.51%	0.02%
R50	32.63%	11.38%	9.41%	1.18%
R100	25.53%	8.03%	15.43%	0.62%
R150	21.80%	9.37%	9.28%	-1.40%
Scenario	HeS2			
	SI_max	CI_max	SI_eff	CI_eff
R10	24.12%	4.35%	8.36%	2.49%
R50	43.03%	1.40%	23.75%	0.01%
R100	90.97%	4.56%	49.13%	1.81%
R150	122.47%	9.12%	62.54%	-0.22%

C.3 Solution comparison in HoS1

Table C.3 presents the comparison of the base solution and the Pareto solutions in HoS1, which are the corresponding percentages visualized in Figure 4.11.

Table C.3: Comparison of the base solution and the Pareto solutions in HoS1

HoS1	Generalized cost	Cost	Time	Delay	Emission	Transshipment	Satisfaction
S1	24.76%	25.35%	-10.59%	14.05%	67.09%	-18.56%	26.98%
S2	22.40%	19.79%	-15.13%	44.26%	54.01%	-22.20%	26.84%
S3	17.07%	16.10%	-13.39%	24.01%	38.98%	20.75%	26.28%
S4	12.65%	15.90%	-7.38%	-22.24%	39.29%	22.20%	25.93%
S5	11.89%	7.96%	-6.86%	48.44%	27.74%	2.18%	20.46%
S6	9.11%	7.80%	-7.25%	19.99%	25.29%	22.93%	18.72%

C.4 Solution comparison in HeS1

Table C.4 shows the corresponding percentages visualized in Figure 4.14.

Table C.4: Comparison of the base solution and the Pareto solutions in HeS1

HeS1	Generalized cost	Cost	Time	Delay	Emission	Transshipment	Satisfaction
S1	9.22%	-4.18%	-7.29%	-40.01%	18.40%	2.30%	23.46%
S2	1.66%	-0.33%	3.97%	-5.92%	10.71%	-6.30%	22.84%
S3	0.99%	5.11%	1.33%	15.73%	9.53%	-13.20%	22.41%
S4	0.67%	-4.35%	1.93%	-17.88%	7.23%	-0.79%	21.36%
S5	0.66%	-4.03%	9.45%	-16.69%	6.88%	5.19%	18.47%
S6	-3.62%	-13.04%	5.49%	-38.10%	-1.05%	17.60%	18.39%