Synchromodality in the Physical Internet: Real-time Switching in a Multimodal Network with Stochastic Transit Times

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Abstract: *Environmental concerns raise the need for more efficiency and sustainability in the freight transportation sector. For this purpose, the Physical Internet is introduced, which aims to connect logistics networks into one hyperconnected supernetwork. To transport freight over such an integrated network, the innovative concept of synchromodality is presented. Synchromodality is defined by the usage of multiple modalities when planning shipments, where real-time switching between transportation modes is possible. In this work, we introduce a synchromodal planning model that constructs optimal transportation routes in a multimodal network with stochastic transit times, formulated as a mixed-integer linear programming problem. To cope with the transit time stochasticity, transportation routes are adapted in accordance to real-time information about the transit time outcome. In a numerical study, we demonstrate the potential advantages that synchromodality entails in terms of costs, service quality and environmental impact.*

Keywords: *Physical Internet, synchromodality, multimodal network, stochastic transit times, optimization, mixed-integer linear programming*

1 Introduction

The logistics industry and its ecological footprint cause an increased pressure for more efficient and sustainable operations. In 2015, the transportation sector represented 18% of all man-made CO_2 emissions, with freight transportation accounting for almost half of these emissions (ITF, 2017). Moreover, if current practices are pursued, the OECD projects a 60% increase in transportation emissions by the year 2050, primarily driven by growing freight transportation emissions. The European Commission strives to limit further environmental damage and is determined to transition to a low carbon economy by the year 2050. The roadmap towards achieving this target enforces the transportation sector to cut its emissions by at least 60% (European Commission, 2011). Consequently, a fundamental change is needed in freight transportation operations to achieve the desired CO_2 emissions reductions.

In order to transition towards more efficiency and sustainability in the freight transportation sector, Montreuil (2011) introduced the holistic concept of the Physical Internet. The Physical Internet, inspired by the digital internet, aims to make the global logistics system more connected, leveraging technologies and algorithms. As such, separate logistics networks and services are integrated into one hyperconnected network, which includes multiple transportation modes.

Transporting freight over such an integrated network raises the opportunity to realize a modal shift, which is a promising method to accomplish significant decarbonization in the freight transportation sector (McKinnon, 2016). This modal shift implies that transportation modes such as rail and barge transportation gain importance over road transportation, because they are less carbon-intensive. Currently road transportation prevails, representing approximately three-quarters of all inland freight transportation in the EU (Eurostat, 2018), in spite of having the highest carbon intensity per ton-km. It is then rather evident that increasing the share of alternative transportation modes can result in substantial carbon emission reductions. In fact, one of the key goals of the Transport 2050 plan is a 50% shift from road to rail and barge transportation by 2050. In addition, these transportation modes are often available at a lower unit transportation cost, which is even more favorable for the companies involved. However, greener transportation modes are typically less flexible as they have longer shipping times and require larger quantities to make them economically advantageous, which makes road transportation favored again.

Up to now, the modal shift towards more sustainable transportation modes has been rather limited. Unimodal road transportation is still the most preferred freight transportation mode. Its flexibility and speed cause road transportation to be perceived as superior and create a barrier to use other transportation modes, regardless of the advantages offered by these are rather limited, as it is a relatively new concept. The purpose of this paper is to develop a model that supports an LSP in constructing the optimal transportation routes for a set of orders, with the objective of minimizing total transportation costs. Our model includes stochastic transit times to reflect the reliability of transportation modes. For instance, an unreliable rail system can result in occasional delays and consequently more variation in the rail transit times. Adapting routing decisions to real-time information can assist to cope with this stochasticity. The implementation of synchromodal planning while dealing with stochastic transit times has not yet been studied. As such, we contribute to the literature with this work, while providing insight in the potential cost and environmental benefits of synchromodality.

2 Literature review

Transportation models can be classified under different levels, depending on their planning horizon, as proposed by Crainic and Laporte (1997). At the operational (short-term) planning level, models operate in a dynamic environment and include the time dimension. Decisions are made in response to real-time data that becomes available at every time step. Given the features of synchromodality, the model developed in this work is classified under the operational planning level. Literature reviews on multimodal freight transportation planning acknowledge that there are not many models at the operational level yet (SteadieSeifi, Dellaert, Nuijten, van Woensel & Raoufi, 2014; Van Riessen, Dekker & Negenborn, 2015). This raises the opportunity to contribute to the literature by developing the proposed model of this work. Accordingly, existing models for synchromodality at the operational level are reviewed, as this is the planning level to which this work contributes.

Several papers deal with uncertainty regarding the freight demand in a synchromodal system. Xu, Cao, Jia & Zang (2015) determine the optimal container capacity allocation at an operational level, where overage and shortage in capacity are penalized. Perez Rivera & Mes (2016) decide on selecting services and transfers to transport freight to their destination, while minimizing cost over a multi-period horizon. Both models assume that there is probabilistic knowledge about the demand arrivals. Nevertheless, the model of Xu et al. (2015) does not apply in great extent to this work. The model only optimizes current capacity decisions to the given demand probability but does not allow to adapt plans afterwards. In this regard, the model of Perez Rivera & Mes (2016) is far more interesting, as it also allows to adjust the planning at each time step. Again, decisions are made in consideration of the probability on future demands, where the entire planning horizon is taken into account. However, only the part of the transportation plan related to the current decision moment is implemented. In the next period, decisions are optimized in response to the newly available demand information. On this subject, Perez Rivera and Mes show applicable features on modeling the decision variables in a multi-period planning horizon. Moreover, both models are noteworthy for the fact that they anticipate uncertainty through probabilistic knowledge. In the problem setting of this work, a similar approach can be implemented to anticipate the stochasticity of the transit times when optimizing the transportation plans.

Other research focuses on planning adaptation when dealing with disturbances. Van Riessen, Negenborn, Dekker & Lodewijks (2013) look into service disturbances, such as early service departure, late service departure and service cancellation. In their work, they construct the transportation planning for one week and adapt it whenever a service disturbance occurs. Planning decisions are optimized in response to new information that becomes available, which is similar to the approach of Perez Rivera & Mes (2016). However, the proposed model only considers adjusting the planning when there is a disturbance in the weekly network service design, otherwise the plan is executed as initially planned. Thus, van Riessen et al. (2013b) await the occurrence of disturbances, whereas we take an anticipatory stance by incorporating the transit times stochasticity. Nevertheless, it is interesting to observe once again that the literature implements adaptation of the transportation plan based on new information.

Another study implementing adaptive planning is the work of Li, Negenborn & De Schutter (2015), which deals with disturbances concerning changes in demand flow and traffic conditions that influence the transit time. Their model decides on the optimal multimodal container flow at every time step of the planning horizon in order to minimize costs and is modeled as a linear programming problem. Yet, only the decisions for the current time step are implemented, which allows to adapt the planning in future periods. Uncertainty in demand flow and traffic conditions is tackled by using an estimate of their future values, and these estimates are then taken into account when optimizing the problem. In the problem of this work, it is not adequate to merely use one single estimate for the transit time between two terminals. The reasoning is that it is known that different transit times can occur. Therefore, the different transit time scenarios and the corresponding probability distribution need to be considered when making decisions. This work aims to address the stochasticity accordingly, while the approach of Li et al. (2015) does not allow to anticipate that parameters can take on different values.

includes the existing legs between terminals for all transportation modes. A leg $(i\ j\ m)$ in set $\mathcal{A}$ is therefore defined by the two terminals (i) and (j) it connects and the transportation mode it represents (m). Given this network description, a transportation route essentially consists of a sequence of legs that connects the origin terminal to the destination terminal of the order.

An example of a multimodal network in this representation is illustrated in Figure 1. The example models three transportation modes: truck (T), barge (B) and train (R). According to this example, the sets are:

$\mathcal{N}_o$ $\mathcal{N}_t$ $\mathcal{N}_d$ $\mathcal{N}$ $\mathcal{N}_o \cup \mathcal{N}_t \cup \mathcal{N}_d$

$\mathcal{A}$

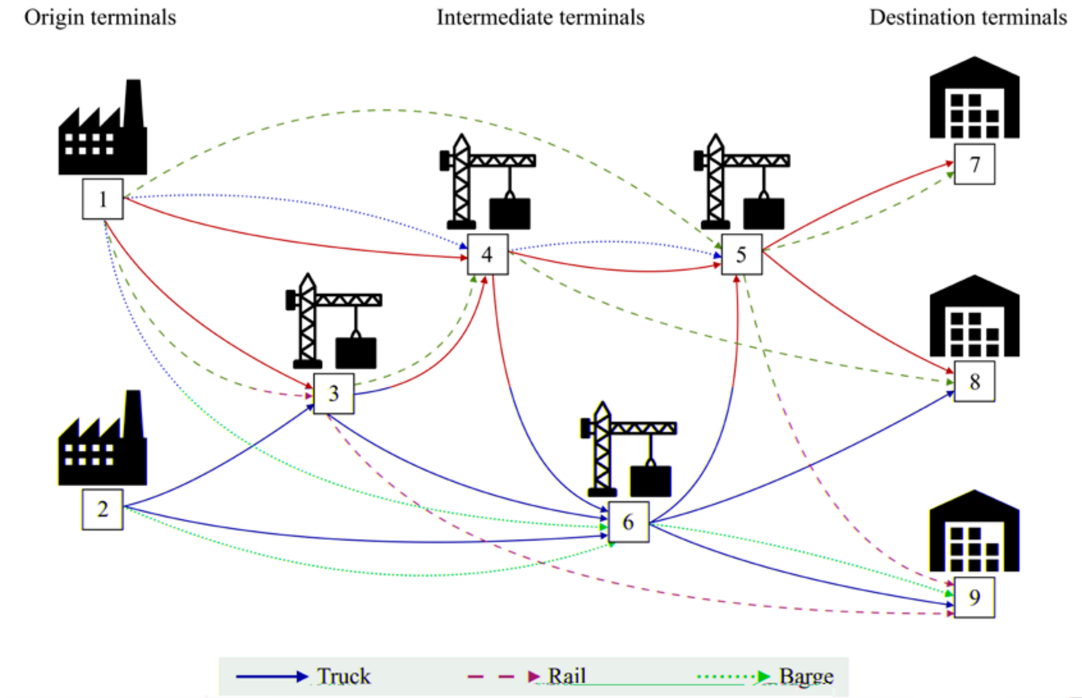


Figure 1: Example of the network representation.

The network has several characteristics that are relevant for the transportation planning problem. With respect to the transportation legs, every leg has a variable transportation cost $(c^V_{i\,j\,m})$. Furthermore, the legs are characterized by a transit time $(l_{i\,j\,m})$, represented as a discrete number of time periods. This work considers a network in which these transit times are stochastic. The stochasticity is modeled through a number of transit time scenarios (S) for each leg, where each scenario has a known probability $(p^s_{i\,j\,m})$. The model is built for stochastic transit times; however, it implicitly covers the case of deterministic transit times, in which the probability of a certain transit time realization equals one.

The terminals of the network also have features that need to be taken into account. Transshipment costs $(c^T_{g\,m})$ are incurred whenever a freight unit is transshipped from transportation mode g to m at an intermediate terminal. All these network characteristics are taken as input parameters for the transportation planning problem.

3.2 Model description

When implementing synchromodality, it is critical that the LSP provides the transportation service at the lowest possible price that attains an acceptable service quality to convince shippers to make bookings (Pfoser et al., 2016; Verweij, 2011). To this end, the model constructs transportation routes with the objective of minimizing total costs. These costs include the variable transportation costs, the terminal transshipment costs, and a penalty that is incurred when an order exceeds its due date. Including a penalty for late delivery ensures that the model strives to reach the due date. How much the LSP is penalized for late delivery depends on the relative importance of on-time delivery to a low booking price.

The LSP determines the optimal transportation route for every order that needs to be shipped. Each order is characterized by an origin terminal (o_n), a destination terminal (d_n), a number of freight units (f_n) and a number of periods until the due date k_n. In the model, it is assumed that orders are not split up during the transportation, such that the customer receives the entire order at once. This way, the customer can be sure that the shipment contains the requested number of units, and the receiving procedures, such as unloading or inspection, only need to be performed once.

Transportation routes are optimized in a network which features stochastic leg transit times, with a predefined probability distribution over the possible transit time scenarios. These transit times are expressed in terms of time periods, so the LSP is actually planning over a time horizon. Consequently, it is required to add a time dimension to the planning decisions, in order to clarify which routing decision is made at which time step. In the optimization model, the planning horizon is expressed as a number of time periods (T) and is set at least equal to the longest path that exists in the network, such that all possible transportation plans fall within this horizon. It is assumed that the network remains the same in all time periods of the planning horizon.

When an order travels a leg with a stochastic transit time, the outcome of the transit time only becomes known upon arrival at the end terminal of the traveled leg. In other words, it is not possible to determine in advance which transit time will occur. Yet, the optimal mode selection for the remainder of the transportation route depends on the realized transit time duration. For instance, when a leg turns out to have a long duration, switching to a faster transportation mode for the next part of the route can compensate for this. On the other hand, it can occur that the actual transit time is short. This earliness can be exploited by switching to slower transportation modes for the rest of the route to benefit from cost advantages. In other words, the realized transit time influences the urgency of the order when it arrives at a terminal, which affects the optimal routing decision. Therefore, the planning must allow that transportation routes are adapted based on real-time information about the actual transit times.

To this end, the model specifies the optimal decision to be taken in a terminal given the time period in which the decision has to be made, which is depends on the transit time realizations. Accordingly, the model actually provides a decision guide conditional on the time period that the decision has to be made. This implies that the LSP only executes the decision that applies to the actual time period he is in, without fixing the subsequent part of the transportation route. This enables him to adapt the transportation plan later on in accordance to transit time information that becomes available in real-time. The optimal transportation decision at a particular time step is determined with the purpose of minimizing the expected costs, given the stochasticity in the transit times. To achieve these expected cost calculations, the model anticipates the optimal decisions that will be made in future periods whenever a particular scenario is realized, while taking the corresponding probabilities into account. The next subsection clarifies how these aspects are implemented in an optimization model.

3.3 Optimization model

The developed optimization model is formulated as a mixed-integer linear programming problem. An overview of the notation is given in Table 1.

Table 1: Notation used in the optimization model.

Sets	
$\mathcal{N}$	Set of terminals
$\mathcal{A}$	Set of legs that connect the terminals
$\mathcal{M}$	Set of transportation modes available in the network
$\mathcal{O}$	Set of orders
$\mathcal{T}$	Planning horizon, $\mathcal{T} = \{0,1,2,\dots,T\}$
$\mathcal{S}$	Transit time scenarios, $\mathcal{S} = \{1,\dots,S\}$
Parameters	
T	Time horizon
S	Number of transit time scenarios per leg
$c^V_{i\,j\,m}$	Variable transportation cost of sending one freight unit over leg $(i\ j\ m)$
$c^T_{g\,m}$	Cost of transshipping one freight unit from transportation mode g to transportation mode m
ρ	Penalty per freight unit per period of late delivery
$l^s_{i\,j\,m}$	Transit time of leg $(i\ j\ m)$ under scenario s as a number of time periods
$p^s_{i\,j\,m}$	Probability of transit time scenario s for leg $(i\ j\ m)$
o_n	Origin terminal of order n
d_n	Destination terminal of order n
f_n	Number of freight units in order n
k_n	Due date of order n
Z	Large value
Decision variables	
$x^n_{i\,j\,m\,t}$	1 if order n is transported over leg $(i\ j\ m)$ at period t, 0 otherwise
Output variables	
$w^n_{i\,g\,m\,t}$	1 if order n is transshipped from transportation mode g to transportation mode m in terminal i at period t, 0 otherwise
$E\ C^V\ {}^n_{i\,j\,m\,t}$	Expected variable transportation cost for order n until reaching its destination when transporting over leg $(i\ j\ m)$ at period t
$E\ C^T\ {}^n_{i\,g\,m\,t}$	Expected transshipment cost for order n until reaching its destination when transshipping from mode g to mode m in terminal i at period t
$E\ \rho\ {}^n_{i\,j\,m\,t}$	Expected penalty cost for order n when reaching destination its destination when transporting over leg $(i\ j\ m)$ at period t

The objective function and constraints of the optimization model are presented as follows.

Minimize

$$\sum_{n\in\mathcal{O}}\sum_{\ i\ j\ m\ \in\mathcal{A}} E\ \ C^{V}\ {}^{n}_{i\ j\ m\ 0}\quad \sum_{n\in\mathcal{O}}\sum_{g\ m\in\mathcal{M}} E\ \ C^{T}\ {}^{n}_{i\ g\ m\ 0}\quad \sum_{n\in\mathcal{O}}\sum_{\ i\ j\ m\ \in\mathcal{A}} E\ \ \rho\ {}^{n}_{i\ j\ m\ 0} \tag{1}$$

The objective function (1) minimizes the total expected cost of the routing decisions made at the start of the planning horizon, t = 0. These expected costs include the variable transportation costs and transshipment costs of the entire route until reaching the destination, and the expected penalty costs for late delivery. This optimization determines the set of optimal decisions over the entire planning horizon, because the expected costs anticipate the optimal decisions that will be made in future periods whenever a particular scenario is realized.

With regard to the constraints to which the model is subjected, there are three sets of constraints: the network flow constraints (2)-(7), the expected cost constraints (8)-(9) and the expected penalty constraints set (10). Each of these sets is presented consecutively.

3.3.1 Network flow constraints

$\sum_{\ o_n\ j\ m\ \in\mathcal{A}} x^{n}_{o_n\ j\ m\ 0}$	$\forall n\in\mathcal{O}$	(2a)
$\sum_{\ i\ j\ m\ \in\mathcal{A}} x^{n}_{i\ j\ m\ 0}$	$\forall n\in\mathcal{O}$	(2b)
$x^{n}_{i\ j\ m\ t} \le \sum_{\ j\ k\ h\ \in\mathcal{A}} x^{n}_{j\ k\ h\ t+l^{s}_{i\ j\ m}}$	$\forall n\in\mathcal{O}\ \forall\ \ i\ j\ m\ \ \in\mathcal{A}\ \forall t\in\mathcal{T}\ \forall s\in\mathcal{S}$	(3)
$\sum_{\ i\ j\ m\ \in\mathcal{A}} x^{n}_{i\ j\ m\ t} \le$	$\forall n\in\mathcal{O}\ \forall i\in\mathcal{N}\ \ \forall t\in\mathcal{T}$	(4)
$x^{n}_{d_n\ d_n\ storage\ T}$	$\forall n\in\mathcal{O}$	(5a)
$\sum_{\ i\ j\ m\ \in\mathcal{A}} x^{n}_{i\ j\ m\ T}$	$\forall n\in\mathcal{O}$	(5b)
$w^{n}_{i\ g\ m\ t+l^{s}_{k\ i\ g}} \ge x^{n}_{k\ i\ g\ t}\quad x^{n}_{i\ j\ m\ t+l^{s}_{k\ i\ g}}$	$\forall\ \ k\ \ i\ \ g\ \ \in\mathcal{A}\ \forall\ \ i\ \ j\ \ m\ \ \mathcal{A}\ \forall t\in\mathcal{T}\ \forall s\in\mathcal{S}$	(6a)
$w^{n}_{i\ storage\ m\ 0} \ge x^{n}_{i\ j\ m\ 0}$	$\forall\ \ i\ \ j\ \ m\ \ \in\mathcal{A}\ \ i\in\mathcal{N}_o$	(6b)
$x^{n}_{i\ j\ m\ t} \in$	$\forall n\in\mathcal{O}\ \forall\ \ i\ \ j\ \ m\ \ \in\mathcal{A}\ \forall t\in\mathcal{T}$	(7a)
$w^{n}_{i\ g\ m\ t} \in$	$\forall n\in\mathcal{O}\ \forall i\in\mathcal{N}\ \forall g\ \ m\in\mathcal{M}\ \forall t\in\mathcal{T}$	(7b)

The first set of constraints (2) to (7) includes the network flow constraints, which ensures that a connected path is formed from the origin to the destination terminal for each order. Constraint (2a) initiates the transportation route by imposing that a leg is selected from the origin terminal of the order at the start of the planning horizon. In addition, constraint (2b) makes sure that this is the only terminal from which a transportation route can be started for the order. Constraint (3) ensures that a connected sequence of legs is selected, while taking the time dimension into account. More specifically, this constraint ensures that whenever a particular leg is selected for an order, another connected leg must be selected at the time the order arrives at the end terminal of the traveled leg. However, there are multiple scenarios for the transit time. For this reason, a connected leg must be selected for every possible arrival time, given the transit time scenarios. Thus, a connected path is constructed for every possible scenario that can occur. Constraint (4) enforces that at most one leg can be selected for an order that is present in a terminal at a time step. This is in line with the assumption that orders are not split up during the transportation

Subsequently, constraint (5a) and (5b) make sure that the order arrives at its destination for all potential scenario instances. With constraint (5a), the model imposes that the order must be in the storage of its destination terminal, i.e. the order has arrived at its destination, by the end of the planning horizon. Subsequently, constraint (5b) imposes that only this storage leg is allowed to be selected for the order at the last time period. Together, these constraints ensure that the order reaches the destination for every possible development of scenarios. Thereafter, constraint (6a) deals with the transshipment variable $w_{i\ g\ m\ t}^{n}$ when transshipping an order from one transportation mode to another in a terminal, while (6b) specifically deals with this variable for origin terminals at time 0. At last, constraint (7a) and (7b) define the relevant decision and output variables as binary.

3.3.2 Expected cost constraints

$$E\ C^{V}{}_{i\ j\ m\ t}^{\ n} \geq c_{i\ j\ m}^{V} f_n \quad \textstyle\sum_s p_{i\ j\ m}^{s} \sum_{\ j\ k\ h\ \in \mathcal{A}} E\ C^{V}{}_{i\ j\ m\ t+l_{i\ j\ m}^{s}}^{\ n} - Z \quad - x_{i\ j\ m\ t}^{n}$$

$$\forall n \in \mathcal{O}\ \forall\ \ i\ j\ m\ \ \in \mathcal{A}\ \forall t \in \mathcal{T} \qquad (8a)$$

$$E\ C^{V}{}_{i\ j\ m\ t}^{\ n} \geq \qquad \forall n \in \mathcal{O}\ \forall\ \ i\ j\ m\ \ \in \mathcal{A}\ \forall t \in \mathcal{T} \qquad (8b)$$

$$E\ C^{T}{}_{i\ g\ m\ t}^{\ n} \geq c_{g\ m}^{T} f_n \quad \textstyle\sum_s p_{i\ j\ m}^{s} \sum_{\ j\ k\ h\ \in \mathcal{A}} E\ C^{T}{}_{i\ m\ h\ t+l_{i\ j\ m}^{s}}^{\ n} - Z\big(\ \ -w_{i\ g\ m\ t}^{n}\big) - Z\big(\ \ -x_{i\ j\ m\ t}^{n}\big)$$

$$\forall n \in \mathcal{O}\ \forall\ \ i\ j\ m\ \ \in \mathcal{A}\ \ i \in \mathcal{N}_t\ \ \forall g \in \mathcal{M}\ \ \forall t \in \mathcal{T} \quad (9a)$$

$$E\ C^{T}{}_{i\ g\ m\ t}^{\ n} \geq \ \textstyle\sum_s p_{i\ j\ m}^{s} \sum_{\ j\ k\ h\ \in \mathcal{A}} E\ C^{T}{}_{i\ m\ h\ t+l_{i\ j\ m}^{s}}^{\ n} - Z\big(\ \ -w_{i\ g\ m\ t}^{n}\big) - Z\big(\ \ -x_{i\ j\ m\ t}^{n}\big)$$

$$\forall n \in \mathcal{O}\ \forall\ \ i\ j\ m\ \ \in \mathcal{A}\ \ i \in \mathcal{N}_o\ \ \forall g \in \mathcal{M}\ \ \forall t \in \mathcal{T} \quad (9b)$$

$$E\ C^{T}{}_{i\ g\ m\ t}^{\ n} \geq \qquad \forall n \in \mathcal{O}\ \forall i \in \mathcal{N}\ \ \forall g\ \ m \in \mathcal{M}\ \ \forall t \in \mathcal{T} \qquad (9c)$$

Constraint (8a) to (9c) define the computation of the expected costs. To begin with, constraint (8a) and (8b) specify the expected variable cost of transporting an order over leg $i\ j\ m$ at time t. The expected variable cost constraint (8a) includes three elements. The first element is the variable cost of selecting the leg, which depends on the cost of the leg and the number of freight units in the order. The second element is forward-looking, as it anticipates the expected cost of the next decision that will be taken when the order arrives at the end terminal of the selected leg. At this point, the corresponding probabilities for the transit time scenarios are taken into account. It is the uncertainty in the transit time outcome that causes the model to work with expectations of the future variable costs. This forward-looking aspect iterates forward until the end of the time horizon. Consequently, it covers the expected cost from the current time period until the end of the time horizon, or stated differently, until reaching the destination terminal, as defined by constraint (5a) and (5b). Finally, the third element of constraint (8a) and (8b) ensure that the expected variable cost only holds a positive value when the leg $i\ j\ m$ is selected for order n at time t, and holds a value equal to zero otherwise.

Given this formulation, the value of $E\ C^{V}{}_{i\ j\ m\ t}^{\ n}$ represents the expected variable cost for order n until reaching its destination when selecting leg $i\ j\ m$ at time t. Accordingly, the value of $E\ C^{V}{}_{i\ j\ m\ 0}^{\ n}$ in the objective function represents the expected variable cost to reach the destination for each routing decision made at the current time step, t = 0.

Constraint (9a) to (9c) are constructed in a similar manner to determine the expected transshipment cost for order n until reaching its destination when transshipping from transportation mode g to m in terminal i at time t. Constraint (9a) applies to intermediate terminals, while constraint (9b) concerns the origin terminals. This formulation ensures that only the transshipment cost from transshipping at intermediate terminals is taken into account. Moreover, both constraints are constructed so that the expected transshipment cost only holds a positive value when there is effectively a transshipment from transportation mode g to m, otherwise constraint (9c) ensures that the cost is set equal to zero. With regard to the forward-looking element, the last part of the formulation makes sure that the forward-looking element only matters for the leg $i\ j\ m$ that is selected.

3.3.3 Expected penalty constraints

$$E\ \rho\ {}^{n}_{i\,j\,m\,t} \geq \textstyle\sum_{s} p^{s}_{i\,j\,m} \sum_{j\,k\,h\ \in \mathcal{A}} E\ \rho\ {}^{n}_{j\,k\,h\,t+l^{s}_{i\,j\,m}} - Z \quad -x^{n}_{i\,j\,m\,t}$$

$$\forall n \in \mathcal{O}\ \forall\ i\ j\ m\ \in \mathcal{A}\ i \in \mathcal{N}_0 \cup \mathcal{N}_t\ \forall t \in \mathcal{T} \qquad (10a)$$

$$E\ \rho\ {}^{n}_{i\,j\,m\,t} \geq\ t - k_n\ f_n \rho - Z\big(\ -x^{n}_{i\,j\,m\,t}\big)$$

$$\forall n \in \mathcal{O}\ \forall\ i\ j\ m\ \in \mathcal{A}\ i \in \mathcal{N}_d\ \forall t \in \mathcal{T} \qquad (10b)$$

$$E\ \rho\ {}^{n}_{i\,j\,m\,t} \geq 0 \qquad \forall n \in \mathcal{O}\ \forall\ i\ j\ m\ \in \mathcal{A}\ \forall t \in \mathcal{T} \qquad (10c)$$

Finally, the expected penalty cost constraints are presented. Constraint (10a) and (10b) determine the expected penalty cost that will be incurred when reaching the destination when selecting leg $i\ j\ m$ at time t. The origin and intermediate terminals are subjected to constraint (10a), which merely includes the forward-looking element until the destination is reached. When the destination is reached, constraint (10b) applies, where the expected penalty cost is calculated as the number of time periods the order arrives late multiplied with the number of freight units and the penalty. When the order does arrive on time, no penalty is incurred, as constraint (10c) sets the penalty cost equal to zero in this case. Constraint (10a) incorporates the incurred penalty costs, as defined in (10b), with the appropriate probabilities. The last element of constraint (10a) or (10b) and constraint (10c) ensure that the expected penalty cost equals zero for legs that are not selected.

4 Numerical study

4.1 Experimental design

A numerical study is performed to illustrate the optimization model and study the performance of synchromodality. The multimodal network configuration presented in Figure 2 is used for the experiment. The network consists of three successive corridors connecting one shipper terminal, two intermediate terminals and one destination terminal, with an equal distance between every two consecutive terminals. Three transportation modes, namely, road, rail and barge transportation, are available between the consecutive terminals.

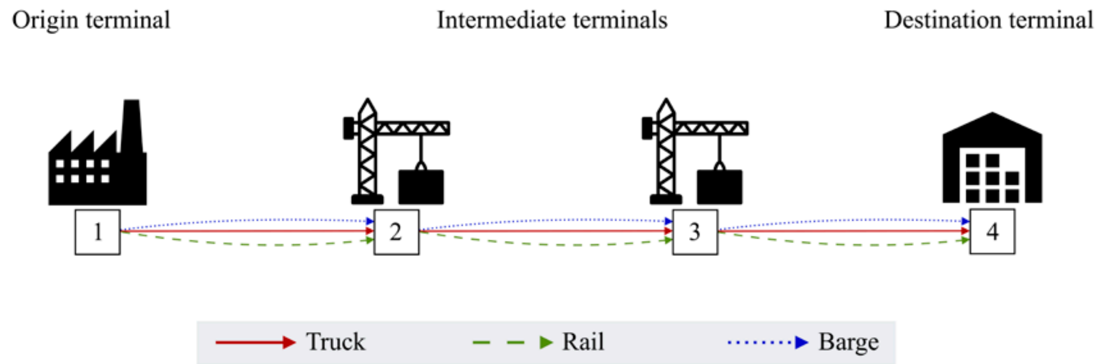


Figure 2: Representation of the network used in the numerical study.

Table 2 provides an overview of the used input parameters, which are composed based on representative industry standards and proportions, extracted from related research papers

(Zhang et al. (2017), Li et al. (2015)) and numbers reported by a leading European logistics service provider (Contargo, 2018). Since the distance between the consecutive terminals is identical for the network in this experiment, the input parameters regarding transit time and cost are as well. The experiment works with three transit time scenarios, for which the probability distribution is assumed to be positively skewed (50% 30% 20%). Transshipment costs equal 20€/TEU when transshipping between two different transportation modes, but no transshipping cost is incurred when there is no modality switch. The penalty per period of late delivery is set equal to 75€/TEU. Furthermore, the planning horizon consists of 27 time periods, which equals the longest possible path that can occur in this network. Finally, the analysis keeps track of the expected CO_2 emissions. The emissions per TEU for every transportation mode in the network are exhibited in Table 2 as well. The experiment considers the transportation planning for ten orders with a due date ranging from 14 to 23. More specifically, the first order is due within 14 periods, the second order is due within 15 periods, and so on. All orders contain one freight unit (i.e. one TEU) and originate from shippers with a transportation demand between origin terminal 1 and destination terminal 4.

Table 2: Variable cost, transit time and CO_2 emission parameters used in the experiment.

Transportation mode	Variable cost (€/TEU)	Transit time scenarios	CO_2 emissions (kg CO_2/TEU)
Road	200	3 / 4 / 5	200
Rail	120	5 / 6 / 7	70
Barge	80	7 / 8 / 9	50

To illustrate the implications of the model, the optimal synchromodal solutions for the orders with due date 18 and due date 20 are displayed in Figure 3. The solutions are presented in a time-expanded representation, where the horizontal axes represent the terminals and the vertical axes represent the time period. As such, this representation shows the optimal decisions to be taken in a particular terminal, given the time period in which this decision has to be made, which depends on the transit time realizations. For instance, this implies the following for the order with due date 18, as shown in the top graph of Figure 3. If the order arrives early at terminal 3 in time period 10, the optimal decision is to opt for barge transportation. However, if it arrives in time period 11 to 13, rail transportation is optimal. If the transit times turn out to have a long duration, causing the order to arrive in time period 14, it is optimal to choose the faster road transportation. These examples clearly demonstrate how a synchromodal transportation policy provides planning adaptability to cope with transit time stochasticity. When an order arrives early at a terminal, it is optimal to opt for a less expensive but slower transportation mode. However, when a longer transit time emerges and the order arrives later at the terminal, the optimal decision is to use a faster transportation mode to compensate for the tardiness. Hence, the solution allows to choose the best transportation mode for the next part of the route dependent on the realized transit times.

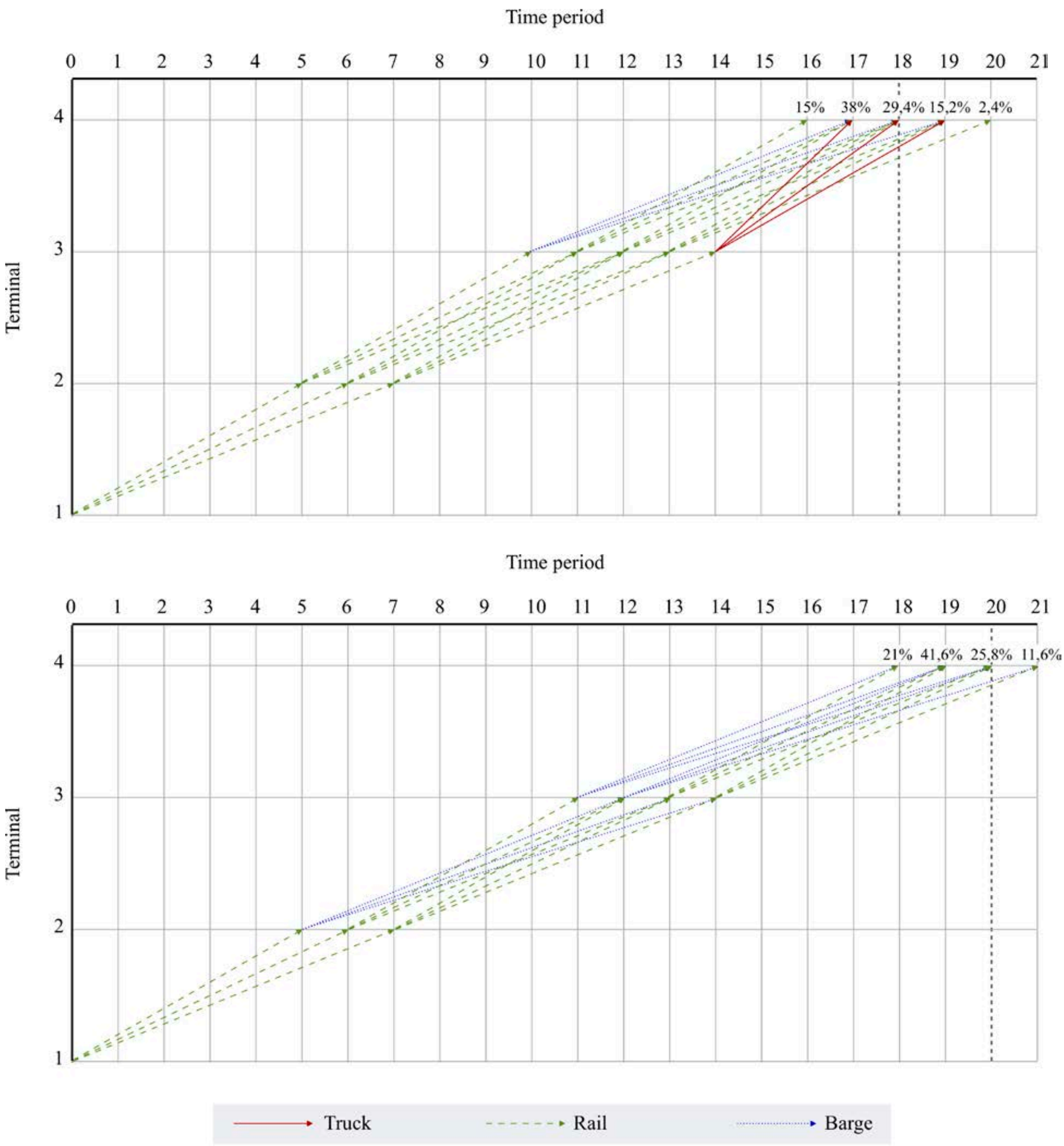
The graphs in Figure 4 summarize the total cost and modal split for every order in the experiment to establish an understanding of the effect of the due date. It is clear that the less urgent the order, the more the transportation route relies on slower, greener and less expensive transportation modes. As a result, the total cost declines as the due date is further in time. From this point of view, shippers can benefit from lower prices when they arrange their shipments to have more extended due dates.

4.2 Analysis

To analyze the performance of a synchromodal transportation system, five different transportation policies are executed for the proposed network. Subsequently, the different policies are compared with regard to expected costs, service quality, modal split and emissions. This way, insight can be gained in the advantages that synchromodality entails. The following policies are evaluated:

(1) Unimodal road transportation
(2) Unimodal rail transportation
(3) Unimodal barge transportation
(4) Multimodal transportation, without the possibility of real-time switching
(5) Synchromodal transportation

Policies (1) to (3) are trivial, the same transportation mode is used for the entire route from origin to destination. For policy (4), a multimodal setting is considered without the real-time aspect of synchromodality. This implies that transshipping to another transportation mode is allowed at the intermediate terminals, yet, the switch cannot be dependent on the time the order arrives at the intermediate terminal. In other words, the shipping route is planned in advance and cannot depend on the transit time outcome. Comparing policy (4) and (5) gives insight in the value of the additional planning flexibility that real-time switching brings along,



which characterizes synchromodality.

Figure 3: Time-expanded representation of the synchromodal solutions for the orders with due date 18 and due date 20 in the experiment. The horizontal axes represent the terminals while the vertical axes represent the time period. The solution shows the optimal decision to be taken in a terminal, given the time period in which the decision has to be made, which depends on the transit time realizations.

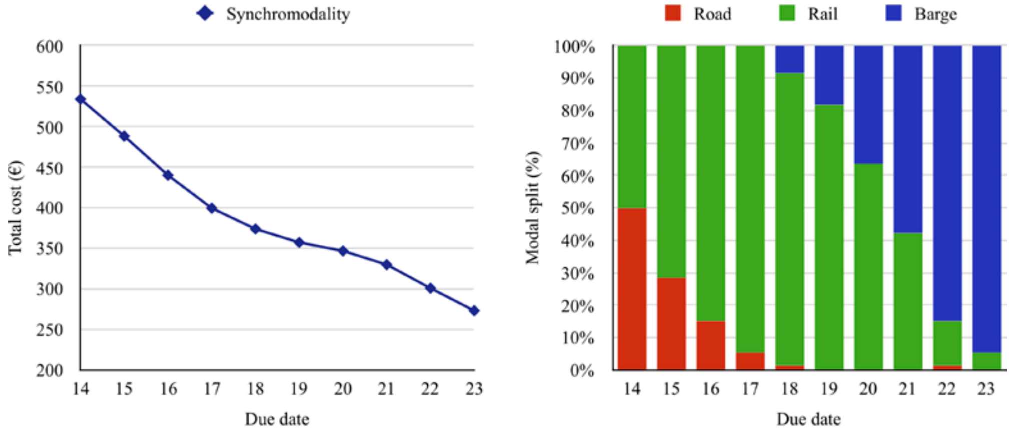


Figure 4: The results for the orders in the experiment, with due dates ranging from 14 to 23. The left panel shows the expected total cost for every order with the corresponding due date in the experiment. The right panel exhibits the expected modal split for every order.

Table 3 reports the results of the experiment for the different transportation policies. Total cost and emissions are expressed as the sum over all orders, while the other factors are expressed as the average over the set of orders. Periods overdue measures the average number of periods an order is expected to arrive late at its destination, and is used as a measure of service quality, where a lower value signifies a higher service quality. The measure is calculated as the probability that the order exceeds the due date multiplied with the lateness whenever this is the case. In this way, the periods overdue measure combines the likelihood and the severity of the due date overrun.

Table 3: Results of the experiment for the different transportation policies in terms of expected values. Total cost and emissions are expressed as the sum over all orders, the other factors are expressed as the average over the set of orders.

Transportation policy	Total cost (€)	Periods overdue	Emissions (kg CO_2)	% Road	% Rail	% Barge
(1) Unimodal road	6000,60	0,0008	6000,0	100%	0%	0%
(2) Unimodal rail	4145,25	0,7270	2100,0	0%	100%	0%
(3) Unimodal barge	5895,00	4,6600	1500,0	0%	0%	100%
(4) Multimodal	3947,40	0,5432	2200,0	6,67%	66,67%	26,67%
(5) Synchromodal	3844,98	0,3173	2313,5	10,10%	59,83%	30,07%

Firstly, these results demonstrate the advantage of using a synchromodal transportation system compared to a unimodal road, rail or barge transportation policy. With synchromodality, a significantly lower emission level is obtained than with unimodal road transportation, which is often the policy used in practice. Moreover, shipments are carried out at roughly two thirds of the costs. With regard to the slower and greener modalities, synchromodality results in a substantially better service quality, indicated by a smaller number of expected periods overdue.

Subsequently, benchmarking synchromodality against multimodal transportation provides insight in the additional value of real-time adaptation when combining multiple modalities in the transportation route. Multimodal transportation already manages a cost reduction compared to unimodal road and a service quality improvement compared to unimodal rail or barge, yet, the improvements are limited. Allowing transshipments to depend on the arrival time at the terminal results in an additional service quality improvement, measured by a 40% decrease in periods overdue, while delivering the orders at an even lower cost. The underlying reason is that routing decisions can be responsive and adapt to the real-time conditions. Consequently, synchromodality allows the LSP to provide transportation services at a favorable price, while offering a reasonable service quality. This way, shippers are more attracted to book the services of the LSP, as an inadequate service quality often refrains them from doing so. However, it has to be noted that synchromodal transportation does rely more on road transportation in order to better respect the due dates, leading to an increase of 5% in carbon emissions compared to the multimodal case. Nevertheless, emissions remain far below the unimodal road emissions, and thus synchromodality definitely gives rise to a considerable environmental benefit. These results confirm that synchromodality entails a combination of advantages that allows to deviate from unimodal road transportation, realizing an environmentally favorable modal shift.

To better understand the value of real-time routing decisions under different parameter values, sensitivity analyses are performed for several input parameters. Firstly, the impact of the penalty per period of late delivery is investigated. The graphs in Figure 5 represent the results for different values of the overdue penalty, showing the following. When the penalty is raised, the number of periods an order is expected to be overdue decreases, as depicted in the middle panel of Figure 5. This is a logical consequence, as a higher penalty implies that it is more costly for an order to arrive late. To achieve this more punctual compliance to the due date, the transportation routes substitute rail and barge for the respectively faster road and rail transportation. This can be seen in the modal splits shown in the right panel of Figure 5. As a result, total costs increase, as displayed on the left panel of Figure 5. Thus, depending on the relative importance of service quality to low costs, the penalty can be set accordingly. For multimodal transportation, costs increase more steadily than for synchromodal transportation, while synchromodality is superior on service quality as well from a penalty of 50 and onward. Consequently, the higher the penalty, the more advantageous synchromodality becomes compared to multimodality.

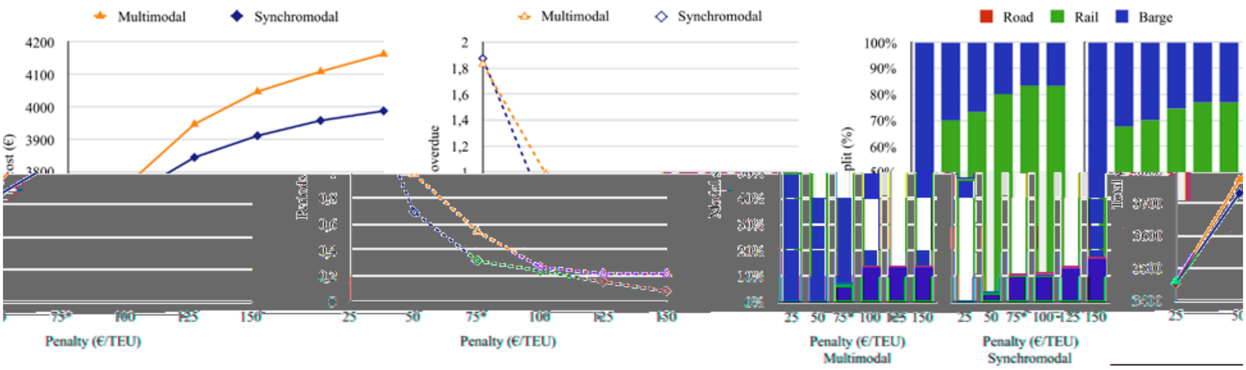
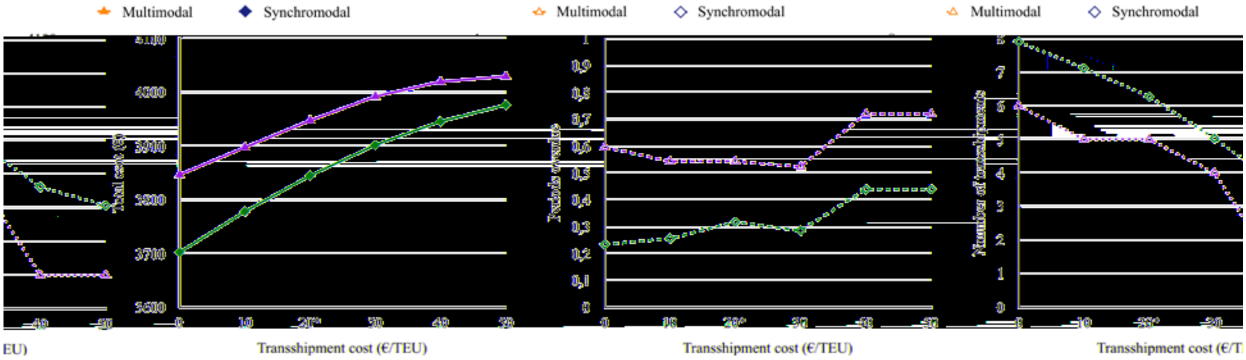


Figure 5: Sensitivity analysis for the penalty per period of late delivery. All graphs show the result for different penalty values for both the multimodal and synchromodal transportation policy. The asterisk indicates the base case setting. The left panel shows the total cost over all orders in the experiment. The middle panel exhibits the average number of periods overdue. The right panel presents the modal split.

Furthermore, a sensitivity analysis is performed for the transshipment cost. Figure 6 exhibits the results in terms of total costs, number of periods overdue and number of transshipments.



These results demonstrate the impact of a reduction in transshipment cost. For synchromodality, this implies that transportation routes can be responsive to the real-time conditions at a lower cost. As a result, more transshipments are made to adapt the routes better to the transit time outcome. This can be observed on the right panel of Figure 6, depicting the expected number of transshipments over all orders. Moreover, when transshipment costs go down, total costs decrease more steadily for synchromodality. Therefore, the lower the transshipment costs, the more beneficial a synchromodal policy becomes in comparison to a multimodal policy. In addition, the middle panel of Figure 6 shows that synchromodality maintains a better performance in terms of due date overrun, regardless of the transshipment cost.

Figure 6: Sensitivity analysis for the transshipment cost. All graphs show the result for different transshipment cost values for both the multimodal and synchromodal transportation policy. The asterisk indicates the base case setting. The left panel displays the total cost over all orders in the experiment, showing how synchromodal transportation is more beneficial when the transshipment cost is lower. The middle panel exhibits the average number of periods overdue. The right panel presents the total number of transshipments over all orders.

At last, the effect of a CO_2 emission tax is investigated. The carbon tax is expressed in euro per metric ton CO_2 and the emission values from Table 2 are used. Figure 7 displays the results of this analysis, whereby the carbon tax ranges from 0 €/ton CO_2 to 400€/ton CO_2. A first consequence of an increasing carbon tax is a rise in total costs, as the costs of all transportation modes go up. This is shown on the top left graph of Figure 7. Moreover, the tax induces an increase in the relative cost of road transportation, as road transportation has a higher carbon intensity and therefore incurs a higher tax in absolute terms. As a result, the cost difference between the transportation modes increases as the carbon tax goes up, making rail and barge transportation relatively more attractive in terms of costs. This diverging effect on the costs can be seen on the bottom left graph of Figure 7.

Accordingly, a carbon tax supports the objective of improving the modal split. However, to make road transportation disadvantageous enough to shift transportation away from road towards rail and barge, the carbon tax needs to be at least 100€/ton CO_2 in the experiment. In this case, the synchromodal policy reacts to the tax by reducing the share of road transportation. For the multimodal policy, a slightly higher carbon tax of 125 €/ton CO_2 is required. The change in modal split can be seen on the right bottom graph of Figure 7, while the top right graph depicts the corresponding emissions. The results support the findings of van den Driest, van Ham and Tavasszy (2011), stating that the CO_2 emission tax has to be quite high in order to establish a change in modal split. In reality, on the other hand, the implemented carbon taxes are often set far below these impacting values (World Bank &

Ecofys, 2018). Furthermore, in order to ultimately transition to a transportation system that eliminates road transportation, the carbon tax needs to take on a value of 325€/ton CO_2 and 400€/ton CO_2 for respectively a multimodal and synchromodal policy.

Nevertheless, it has to be noted that the shift towards more sustainable transportation modes also implies a shift to slower modes. This leads to an increase in the expected periods overdue, as presented in the top middle graph of Figure 7. Again, a consistently lower number of periods overdue is observed for synchromodality, verifying that the synchromodal policy achieves a better service quality regardless of the carbon tax.

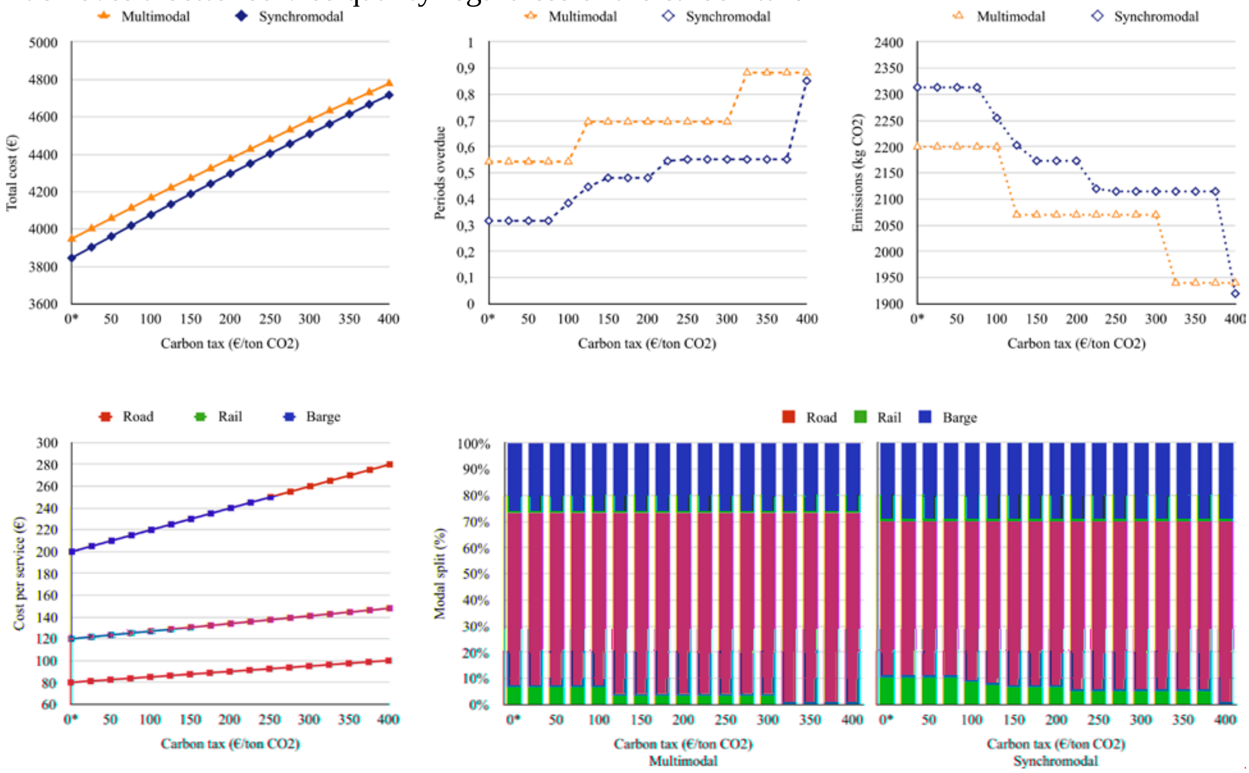


Figure 7: Sensitivity analysis for the carbon tax. All graphs show the result for different tax values for both the multimodal and synchromodal transportation policy. The asterisk indicates the base case setting. The top graphs respectively show the total cost over all orders, the average number of periods overdue and the emissions over all orders. The bottom graphs exhibit the cost per service for every transportation mode (left) and the modal split (right).

This numerical study shows how synchromodality consistently performs better in terms of costs, where the relative cost reduction is larger when the penalty cost is higher and when the transshipment cost is lower. Moreover, the increased planning adaptability facilitates in respecting due dates, which generally results in a lower number of periods overdue for the synchromodal transportation policy.

5 Conclusion

Synchromodal planning can consistently reduce the total transportation cost in comparison to unimodal and multimodal transportation policies. Moreover, it is observed that synchromodality realizes significant emission reductions compared to unimodal road transportation and service quality improvements compared to unimodal rail or barge transportation. The value of real-time planning adaptation is investigated by benchmarking synchromodality to a multimodal transportation policy. The results show that synchromodality outperforms multimodality with regard to transportation costs and service quality, which are the two most important features in order to attract shippers. This verifies that synchromodality allows to induce a shift towards more sustainable transportation modes at an advantageous cost without compromising on service quality. Furthermore, sensitivity analyses suggest that the relative improvements that synchromodality entails, thanks to its planning adaptability, increase when the overdue penalty goes up or when the transshipment cost goes down. The carbon tax analysis indicates that at least a tax of 100€/ton CO_2 is required to encourage a further modal shift and reduce emissions.

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