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To cite this article: Emrah Demir, Martin Hrušovský, Werner Jammerneegg & Tom Van Woensel (2019) Green intermodal freight transportation: bi-objective modelling and analysis, International Journal of Production Research, 57:19, 6162-6180, DOI: [10.1080/00207543.2019.1620363](https://doi.org/10.1080/00207543.2019.1620363)

To link to this article: <https://doi.org/10.1080/00207543.2019.1620363>



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Published online: 28 May 2019.



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## Green intermodal freight transportation: bi-objective modelling and analysis

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(Received 30 December 2017; accepted 17 February 2019)

Efficient planning of freight transportation requires a comprehensive look at wide range of factors in the operation and management of any transportation mode to achieve safe, fast, and environmentally suitable movement of goods. In this regard, a combination of transportation modes offers flexible and environmentally friendly alternatives to transport high volumes of goods over long distances. In order to reflect the advantages of each transportation mode, it is the challenge to develop models and algorithms in Transport Management System software packages. This paper discusses the principles of green logistics required in designing such models and algorithms which truly represent multiple modes and their characteristics. Thus, this research provides a unique practical contribution to green logistics literature by advancing our understanding of the multi-objective planning in intermodal freight transportation. Analysis based on a case study from hinterland intermodal transportation in Europe is therefore intended to make contributions to the literature about the potential benefits from combining economic and environmental criteria in transportation planning. An insight derived from the experiments conducted shows that there is no need to greatly compromise on transportation costs in order to achieve a significant reduction in carbon-related emissions.

**Keywords:** green logistics; freight transportation; intermodal transportation; CO<sub>2</sub>-equivalent emissions; transport management system software

### 1. Introduction

Planning of transportation operations and their execution in an efficient way is a complex process requiring coordination of different activities. An analysis of transportation processes from Treitl et al. (2013) shows that even if goods are transported directly by one vehicle from an origin to a destination, a number of steps have to be fulfilled: starting with a transportation request from customer including the goods to be transported, their origin, destination and the time windows for pick-up and delivery, it is necessary to find a suitable vehicle to execute the transport. In addition to that, several administrative and invoicing processes are also necessary.

The complexity is even increased in cases where different transportation modes are combined. Here additional actors come into play with their own requirements that have to be considered in the proposed transportation plan. The growing number of requirements increases the risk of transportation delays resulting in cancellation of the original plan and the need for re-planning. Therefore, transportation planners prefer road transportation before other alternatives where they have less experience (e.g. intermodal transportation) since they perceive the performance of these alternatives as insufficient (StadieSeifi et al. 2014).

Although road transportation is considered as a flexible transportation mode due to the dense network and possibilities to use many alternative routes (Bowersox, Closs, and Cooper 2010), it is also negatively influenced by the increasing traffic volumes and limited infrastructure capacities. As a result, multiple delays and disruptions decrease the reliability of this transportation mode. Moreover, the ecological aspect of the transportation is becoming more important since the carbon dioxide equivalent (CO<sub>2</sub>e) emissions from transportation form a big part of the total emissions that are responsible for the climate change and its negative impacts (Demir, Huang, and Scholts 2015). Therefore, it might be convenient to consider other transportation alternatives than only road transportation.

One of the alternatives is the intermodal transportation in which goods are transported in standardised loading units that are transhipped between different transportation modes (StadieSeifi et al. 2014). Although organising and monitoring

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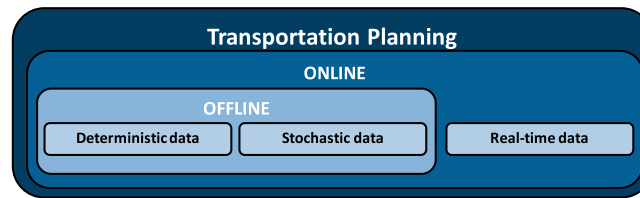


Figure 1. A categorisation of input data for transportation planning (based on Arikan et al. (2014)).

of intermodal transportation chains require more coordination effort and the reliability of the system might be lower in comparison to single mode transportation, there exist methods which are able to consider possible disruptions by creating robust transportation plans and reacting quickly in case of events which make the transportation plan infeasible.

Transportation planning should address a number of interrelated problems covering strategic-, tactical- and operational-level challenges. In this regard, Service Network Design (SND) problem deals with both tactical and operational issues. As shown in the reviews of Bektaş and Crainic (2007) and Mathisen and Hanssen (2014), numerous mathematical models have been developed to solve such complex SND problems (Agamez-Arias and Moyano-Fuentes 2017). However, green logistics in this context is still not sufficiently covered (Demir et al. 2016). Besides that, the presented optimisation models usually consider basic distance-related emissions models to optimise the problem and do not include the actual characteristics of fuel consumption. In the study of Qu, Bektaş, and Bennell (2016), the authors studied an intermodal transportation problem with a consideration of emissions and transfers. An integer programming formulation with distance-based emissions model is formulated and a hypothetical case study of the United Kingdom is investigated. In another study, Resat and Turkey (2015) studied a bi-objective optimisation model (i.e. transportation cost and time) for integrating road, rail and sea transportation modes in a case study. The authors formulated the intermodal problem as a mixed-integer optimisation problem that accounts for time and congestion dependent vehicle speeds. Demir et al. (2016) studied the green intermodal freight transportation problem with travel time uncertainty. The authors proposed a sample average approximation method for solving the investigated intermodal problem. Later, Hrušovský, Demir, and Jammernegg (2017) studied a more practical version of the SND problem using integrated simulation and optimisation approach in a stochastic and dynamic environment. In another study, Wang, Wang, and Zhang (2017) investigated a dynamic resource allocation problem, in which an intermodal operator attempts to determine the policy that characterises the optimal quantities of each service product allowed to be sold during each time interval within a finite selling horizon. The authors formulated the problem is formulated as a Markov decision process model and a variety of mathematical programming models are developed to approximate it.

Depending on the available data and the time of planning, the planning process can be divided into two phases as depicted in Figure 1.

Offline planning is performed before the start of the transportation when a transportation request is received. In this phase the state of the transportation network at the time of execution is unknown. Therefore, planning can be performed using only deterministic data about the network (e.g. terminals, speed limits) and stochastic data based on historical data from past transportations (e.g. historical travel times, demand fluctuations). In addition to that, if information about planned events (e.g. road maintenance) is already available, these data can be also included into planning. When a disruption of the transportation network is detected after the start of transportation, the online re-planning process has to be initialised. In this case the feasibility of the original plan can be checked and a new plan can be created if needed. In addition to deterministic and stochastic data available for offline planning, real-time data about the current state of the infrastructure and position of vehicles can be taken into account in the online re-planning process (Arikan et al. 2014).

Besides the higher complexity of intermodal transportation planning and the different planning phases, it is also necessary to look at the objectives according to which the transport flows are planned. In this respect the concept of green logistics is becoming more and more important in the field of supply chain management, including activities such as sourcing, procurement or transportation (see, e.g. Dekker, Bloemhof, and Mallidis 2012; Kumar, Teichman, and Timpnagel 2012; Demir, Bektaş, and Laporte 2014b; Demir, Huang, and Scholts 2015; Bektaş et al. 2018). Within this concept, not only economic (i.e. costs) but also environmental (i.e. CO<sub>2</sub>e emissions) criteria and other negative influences of transportation operations on the society (e.g. accidents, noise, congestion, land use) have to be taken into account, which often leads to trade-offs between the considered objectives (Demir, Huang, and Scholts 2015).

The mentioned challenges and available data sources cannot be combined easily in the transportation planning process. Therefore, various Transport Management Systems (TMS) have been developed for companies to optimise their transportation flows and to respond to daily challenges and opportunities (i.e. environmental awareness) (Demir et al. 2013). However, as the survey conducted by Demir et al. (2013) showed, most of the available TMS use a rather simplistic approach which covers a single transportation mode and optimises the plans according to one objective, usually transportation costs. In

some cases also the environmental factor in form of CO<sub>2</sub>e emissions is present, but these emissions are usually calculated ex-post for the cost-optimal plan and not directly used in optimisation. Moreover, the calculation of CO<sub>2</sub>e emissions might differ depending on the methods and assumptions used. As a consequence, the available TMS might not always fulfill the requirements that are necessary for transportation planning in today's world.

In order to reflect the current challenges in transportation planning, this paper discusses the points that can be addressed by the use of better planning algorithms. These points are summarised in Section 2 which discusses the differences between traditional and green logistics approach. Some of these factors are then addressed in the developed optimisation model and especially in the real-world case study introduced in Section 5. The focus is put mainly on the bi-objective planning and the investigation of trade-offs between costs and CO<sub>2</sub>e emissions for intermodal freight transportation planning. Since there exist different methods for the calculation of CO<sub>2</sub>e emissions in transportation, this paper also discusses in detail the methods which we chose and their assumptions. The scientific contribution of this study is threefold: (i) to discuss the requirements for intermodal transportation planning in the green logistics context, (ii) to introduce a bi-objective variant of the Green Intermodal Transportation Problem by discussing details on emissions from three different transportation modes, and (iii) to test bi-objective techniques to solve the investigated problem on a real-world case study.

The paper is structured as follows. Section 2 compares the current transportation practices and the future directions required for considering the environmental performance of transportation. Section 3 then outlines the modelling methodology used for incorporating environmental criteria into the transportation planning. Section 4 presents the bi-objective intermodal transportation problem which is then applied to a real-world case study in Section 5. Conclusions and future research directions are stated in Section 6.

## 2. Inclusion of environmental approach into intermodal transportation planning

This section provides a brief discussion on the current practices of the transportation planning and directions to improve environmental performance of transportation companies by implementing green logistics approach.

Green logistics includes all activities to observe, measure and minimise the ecological impact of logistics. Transportation planning is now expected to force all stakeholders to address green logistics requirements and not just their own. For example, with an increasing worldwide concern for the environment, freight carriers have started paying more attention to the negative externalities of their operations (Demir, Huang, and Scholts 2015). Among others, these externalities include environmental impact that can be measured in form of carbon dioxide-equivalent (CO<sub>2</sub>e) emissions which have to be measured and calculated accurately. It should be also noted that reducing emissions with a proper implementation brings more advantages than disadvantages for the logistics service providers and freight forwarders. Therefore there is an increasing need to remind these advantages to transportation companies (Dekker, Bloemhof, and Mallidis 2012).

Transportation companies generally use Transport Management System (TMS) software to plan, execute and monitor their transportation activities. Such software packages can be seen as a subset of supply chain management concerning transportation operations and can be located in the core of transportation operations (Seiler 2012). Some of the functionality in the TMS includes automated carrier selection, shipment consolidation, route optimisation, freight estimate optimisation and payments.

In the last decade, transportation companies are searching for new methods and algorithms in TMS software packages to manage their operations for the challenging environment as discussed in Hall and Partyka (2016). For example, the focus on the use of planning tools in real-life environment becomes an essential requirement in transportation planning. More specifically, the real-life world is dynamic and stochastic and information on this setting should be available before the planning activities. Any decision, action or plan built on unrealistic assumptions (e.g. static and deterministic) is bound to be sub-optimal once realised. In this regard, traditional transportation planning is facing fundamental changes in terms

Table 1. Comparison between traditional planning and green logistics approach.

Dimension	Traditional planning approach		Green logistics approach	
	Method	Example	Method	Example
Algorithm	Simple	Local search	Advanced	Global search
Data availability	Deterministic	All parameters	Stochastic	Time uncertainty
Data source	Single	Distance	Multiple	Water level
Mode	Single	Road	Intermodal	At least two modes
Optimisation	Single-objective	Cost	Multi-objective	Time and emissions
Time horizon	Offline	Before execution	Online	After execution

of modelling and implementation. We now present the important differences between the traditional and green logistics approach in Table 1.

- *Algorithm:* The complexity of transportation planning increases as the size of the shipments increases. With increasing complexity, the planning problem turns into a problem with non-deterministic polynomial time that is very difficult to solve in a reasonable time (Toth and Vigo 2014). The solution time increases exponentially with every shipment and planning problems cannot be solved with an exact and optimal end result within a reasonable time by traditional techniques. To solve large-sized optimisation problems, there is a need for advanced solution methodologies such as meta-heuristic algorithms. Hence, there exist many heuristic algorithms, which promise to provide solutions close to the best possible solution (see, e.g. Euchi 2012; SteadieSeifi et al. 2014). Each TMS includes its own heuristic, which is using a specific optimisation algorithm (Hall and Partyka 2016). These optimisation algorithms are opted to improve the solution to overcome the current requirements of transportation planning.
- *Data availability:* Many TMS software tools are available in the market but very often they are based on deterministic data and consideration of real-time and stochastic data is limited (see, e.g. Gendreau, Jabali, and Rei 2016; Ritzinger, Puchinger, and Hartl 2016). Consideration of deterministic and static data regarding the state of the infrastructure, vehicle characteristics or travel times might offer a good planning basis in situations where everything is working normally and transports can be conducted without delays (Zhu and Levinson 2012). However, in the real world there are often many causes for disruptions (e.g. accidents, congestion, low water levels, weather, etc.) which lead to delays and possible need of re-planning requiring high organisational effort and causing higher costs or emissions. In order to reduce the impact of these disruptions they can be taken into account already during planning using the information about the current state of the infrastructure or including data showing historical travel times. In this way a robust transportation plan can be created and the need for re-planning can be reduced.
- *Data source:* An important factor for the quality of the transportation plans is the quality and availability of data (Kitchin 2014). The planning results can be improved by integrating additional data sources. Since there are many events influencing the originally created transportation plan during execution, real-time planning techniques need to be developed in order to be able to react to disruptions and to offer various re-planning alternatives using the real-time data from multiple sources. These sources can be publicly available data about current traffic situation (e.g. TomTom 2018; Waze 2018) which can be used to identify potential unexpected events that might lead to delays. In addition to these simple data sources, software programs that combine different data and record planned and unplanned events can be used to issue alerts if a deviation from transportation plan is recorded (see e.g. Baumgrass et al. (2013) for information aggregation or DiCiccio et al. (2016) for detection of flight diversions). Besides that, recording of historical travel times can help to evaluate the travel time reliability of different alternative routes, as it was shown by Demir, Hrusovsky, and Jammernegg (2017) for road transport.
- *Mode:* One of the phases of planning is the consideration of different modes of transportation (see, e.g. Caris, Macharis, and Janssens 2013; SteadieSeifi et al. 2014). When planning a route between two locations, it may be necessary to use more than one transportation mode for the entire journey. As much as it is necessary to use more than one mode for geographical reasons, it is also necessary to consider this option for accommodating different types of load, size, shape etc., of the goods being transported. Therefore it is essential to consider all possible solutions including intermodal trip planning.
- *Optimisation:* Multi-objective optimisation investigates to what extent we can consider different objectives and optimise them together keeping in mind various constraints (see, e.g. Deb 2014). Many prefer to keep the number of objectives as low as possible to reduce the complexity. However, this is not always the case in real life. Often, multiple objectives have to be considered at the same time for a better solution (e.g. Peidro et al. 2012; Su 2014). In green logistics domain, inclusion of emissions is essential to improve the environmental performance of the transportation activities.
- *Time horizon:* In offline (or static) planning, all forms of input information are required in advance. In online (or dynamic) planning, available real-time information helps to adjust planning solutions and making them more precise and effective (see, e.g. Pillac et al. 2013; Psaraftis, Wen, and Kontovas 2016). Planning starts with the available information and is further processed and improved with the real-time data provided to the TMS software which finally executes the planning. Without considering the real-time data, any green logistics methodology cannot perform well and even leads to worse solutions in real-life environment because of unrealistic assumptions done in planning.

Although all of the presented factors contribute to improved transportation planning, they might be suitable for different situation and planning phases and therefore it is not possible to combine all of them in one optimisation model. As an example, usage of real-time data enables detection of transportation disruptions which require a fast response in form of

an alternative plan in online planning mode and therefore it is not possible to implement a complex global planning model with multiple objectives in these situations. In contrast to that, an initial offline transportation plan has to be created for each received transportation order, where it is usually possible to consider different objectives and alternatives, but only limited real-time data is available since it is created before the transportation starts. As a consequence, this paper focuses on the integration of economic and environmental criteria into offline transportation planning, compares different methods of bi-objective optimisation and investigates the influence of the individual objectives on the resulting transportation plans. In order to achieve this, it is necessary to estimate the input values for each objective accurately, which might be challenging especially for the environmental part. Therefore, the chosen methods for CO<sub>2</sub>e emissions calculation of each transportation mode considered in the case study in Section 5 are discussed in the next section.

### 3. Incorporating the modelling of emissions into intermodal transportation planning

Greenhouse gases (GHGs) are the most studied negative externality of freight transportation. These gases cause atmospheric changes and climate disruptions which are harmful to the environment and pose health risks. The primary transportation-related man-made GHGs in the Earth's atmosphere are carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>), nitrous oxide (N<sub>2</sub>O) and ozone (O<sub>3</sub>). As CO<sub>2</sub> is the dominant man-made GHG, the impact of other gases can also be calculated based on carbon dioxide equivalent (CO<sub>2</sub>e) emissions. Despite the fact that transportation sector is one of the biggest contributors of CO<sub>2</sub>e emissions, this factor is not sufficiently considered in available TMS. This development might be caused by multiple reasons connected to the calculation of emissions:

Firstly, the amount of emissions is dependent on the energy needed for moving the vehicle. Estimating the energy consumption before transportation is problematic as it is dependent on different factors which are not always known. These factors include vehicle characteristics (e.g. weight, engine), route and driving characteristics (e.g. road gradient, driving behaviour), and the amount of goods transported (Barth and Boriboonsomsin 2008; Eichlseder et al. 2009).

Secondly, the scope of emissions considered in calculation has to be determined. In case of transportation, the considered emissions can be limited to emissions from fuel consumption directly in the vehicle (tank-to-wheel, TTW) or can also include emissions from production of the fuel (well-to-wheel, WTW). Consideration of WTW emissions is especially important in cases where electric vehicles are involved since emissions from electricity consumption are equal to zero (Kranke, Schmied, and Schön. 2011). This is also the case in this paper.

Thirdly, the monetary value of CO<sub>2</sub>e emissions is unclear. Since the long-term effects of emissions on climate change cannot be easily predicted, the estimation of emission costs is dependent on different discount rates for future events and risk attitude of the decision makers. As a result, the so-called social costs of carbon emissions are estimated to be between 0 EUR and more than 700 EUR per ton of emissions depending on the model (Anthoff and Tol 2010; Nordhaus 2011). Therefore, the monetary value of emissions cannot be easily compared to transportation costs.

In order to be able to estimate the emissions, a number of different microscopic models requiring detailed inputs have been developed as shown by Demir, Bektaş, and Laporte (2014b). However, these models often require detailed inputs regarding the vehicle and route characteristics, which are not always available. As an alternative, emissions calculators and models based on real-world measurements and recommended values for a typical vehicle are also available (e.g. IFEU 2011). However, these values are often valid only for a certain country (IFEU 2016), the models include only TTW emissions, the calculators are only available for certain transport modes (e.g. PTV 2017), use only average values per transportation mode without the possibility to adjust it according to the real-world situation or use the same methodology for different transportation modes (e.g. NTM (2008) with the same method for IWT and sea shipping). As a result, there is not one perfect model or calculator for all transportation modes, but it is necessary to look for transportation mode-specific methods in order to minimise possible differences between calculated and measured emissions. Although these differences cannot be fully eliminated, because it is not possible to completely include factors such as driving behaviour and traffic situation, models which can be adapted according to the available data can help to improve the emission calculations. Sections 3.1–3.4 describe the methods used in this paper.

#### 3.1. Road freight transportation

Depending on the data availability, the amount of CO<sub>2</sub>e emissions can be estimated using either microscopic or macroscopic models (Demir, Bektaş, and Laporte 2014b). We now provide a macroscopic model presented by Hrusovsky et al. (2013) based on DSLV (2013). The total fuel consumption  $E$  (in liter per 100 km) is calculated as the sum of empty-drive  $A$  and freight-related consumption  $B$ . Whereas the empty-drive consumption is mainly dependent on speed and can be calculated as shown by Hausberger et al. (2009), the freight-related consumption is influenced by the load factor. Fuel consumption can be calculated as  $E = A + Bf_L$ , where  $f_L$  is the load factor showing the share of capacity used by the goods transported.

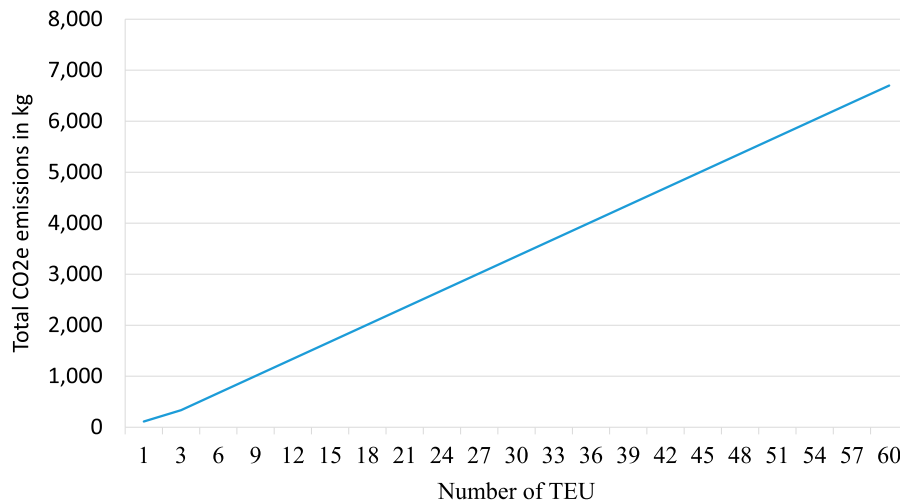


Figure 2. Emissions of a 24–40 tonne heavy duty vehicle in flat conditions (Source: The authors).

In order to include the road gradient into this formula, the emissions have to be multiplied by 1.05 for hilly and 1.1 for mountainous countries. In any case the model assumes a linear relationship between fuel consumption and load factor which is also shown in Figure 2 where the amount of CO<sub>2</sub>e emissions for transporting different number of TEUs for 100 km is displayed. It is noted that CO<sub>2</sub>e emissions can be derived directly from fuel consumption by using a multiplication factor of 3.24 kg CO<sub>2</sub>e emissions per one liter of diesel (WTW emissions) (Kranke, Schmied, and Schön. 2011).

### 3.2. Rail freight transportation

In case of rail transportation the energy consumption is dependent on vehicle characteristics such as rolling and aerodynamic resistance, and the weight of the train. In addition to that, the speed and acceleration profiles and gradient play an important role (Boulter and McCrae 2007). Whereas the emission factor for diesel of 3.24 kg/l is independent of the country, the emission factors for electricity differ significantly as they are dependent on the sources from which electricity is produced in every country (Kranke, Schmied, and Schön. 2011). For example, the emission factor for Greece is relatively high with 0.98 kg/kWh as most of the energy is produced from solid fuels. As a contrast, electricity production in Austria causes only 0.112 kg of emissions per kWh since 70% of electricity is gained from renewable sources (European Commission 2014). In any case the emissions for electricity are much lower in comparison to diesel because the electric train does not produce any TTW emissions and thus only emissions from energy production are reported. Therefore, WTW emissions should be used when comparing different transportation modes.

Although the energy consumption of a train is influenced by different factors, it can be related to its gross weight. The energy consumption for electric trains can be calculated as  $EC = 1200 * GWT^{-0.62}$ , where  $EC$  is energy consumption of the train in kWh and  $GWT$  is its gross weight in tons. This formula can be used especially for trains between 600 and 1800 tons gross weight which is a range typical for container trains. The results are valid for hilly countries and have to be multiplied by 0.9 for flat and by 1.1 for mountainous countries (IFEU 2011).

For the fuel consumption in liters for diesel trains Kranke, Schmied, and Schön. (2011) recommend the following formula  $EC = 0.326 * GWT^{0.38}$ . The resulting emission functions for diesel and electric train on the route between Budapest and Munich (distance of 729 km) are displayed in Figure 3. For electricity, the EU-average electricity emission factor of 0.468 kg/kWh was used (Kranke, Schmied, and Schön. 2011).

### 3.3. Inland waterway freight transportation

Whereas emissions for road transportation can be calculated as a linear function and emissions of trains are dependent on the gross weight of the vehicle, deriving a general emission function for IWT seems to be challenging. The reason is that here it is necessary to consider also the waterway characteristics which might change for each river section. Therefore, the solutions adapted in emission calculation models usually use a fixed average emission factor per ton kilometer (see, e.g. IFEU 2011, 2016) or apply the methodology used for sea vessels also to IWT (NTM 2008), ignoring the additional influencing factors. Although the results of these approaches might be suitable for comparing transportation modes on a global perspective, they might lead to suboptimal decisions when alternatives for a certain transport have to be evaluated.

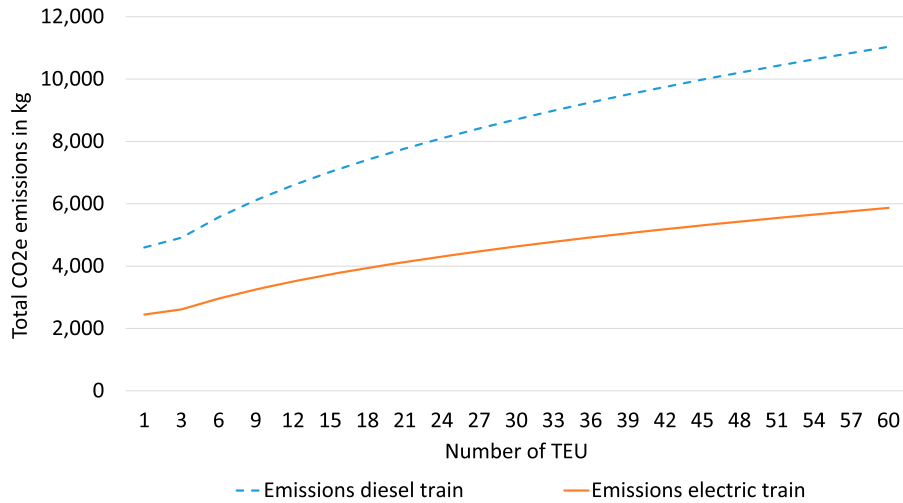


Figure 3. Emissions of diesel vs. electric train between Budapest and Munich (Source: The authors).

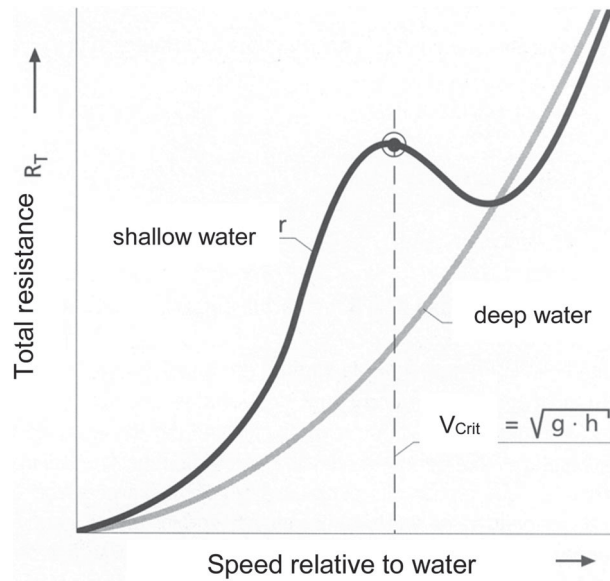


Figure 4. Resistance as a function of speed by (Source: Boulter and McCrae (2007)).

This situation is typical when a company is not interested whether a vessel is in general more environmentally friendly in comparison to train, but has to evaluate which transportation mode it should use for transporting goods between two terminals.

A detailed emission calculation approach for IWT was presented by Boulter and McCrae (2007) who developed a model including all important factors necessary to calculate emissions for a specific route. This approach estimates the power needed to overcome the vessel resistance which is then translated into the energy consumption of the vessel. For this, vessel parameters such as length, breadth, draught and number of propellers have to be known. In addition to that, the waterway characteristics of the route are needed.

The waterway is characterised mainly by its width, water depth and speed of the water. The speed of the water influences the speed of the vessel relative to the water which is important to determine the engine power needed. Especially, in areas with shallow water the resistance is increasing very fast when the speed of the vessel is getting closer to the critical speed as it is shown in Figure 4. The critical speed is defined by the so-called Froude number  $F_{nh} = V/\sqrt{gh}$  where  $V$  is the speed,  $g$  is the acceleration due to gravity and  $h$  is the depth of the waterway. The critical speed is reached when  $F_{nh} = 1$ . Such shallow water sections can be found especially in unregulated parts of the rivers during low-water periods (see e.g. via donau (2007) for Danube). Besides the negative influence on resistance, shallow water sections can also limit the maximal



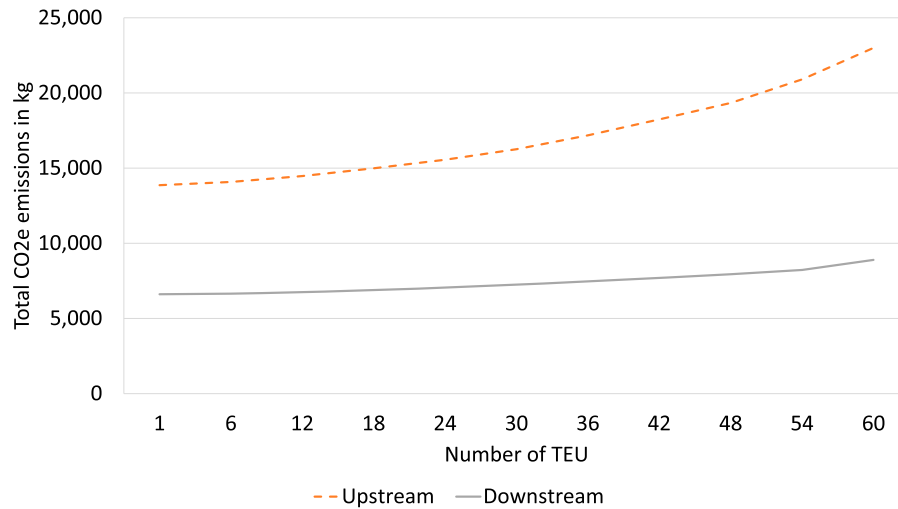


Figure 5. Emissions of a vessel sailing between Regensburg and Budapest (Source: The authors).

possible draught of the vessel and consequently the capacity, further increasing the amount of emissions per unit of cargo. The engine power needed is also influenced by the sailing direction of the vessel since it has to overcome the speed of the water when sailing upstream and can use the speed of the water when sailing downstream.

When all mentioned factors are estimated, the model calculates the power consumption  $P_d$  which has to be multiplied by the specific fuel consumption ( $SFC$ , 190–230 g/kWh for conventional inland vessels) and fuel calorific value  $FCV$ . The total energy consumption can be obtained as  $EC = \frac{P_d * SFC * FCV}{10^3 * V * RL}$ , where  $V$  is speed in km/h and  $RL$  is reference load in tons. Using this formula, it is possible to calculate the energy consumption for a specific trip of a vessel and multiply it with the corresponding emission factors. The resulting emission function is non-linear and therefore the number of containers transported has to be known for calculating emissions per container.

As an example, the emission functions for a vessel with 60 TEU capacity are displayed in Figure 5 for a trip on the Danube between Regensburg (Germany) and Budapest (Hungary). These emission functions are based on data from Marine Traffic (2015) and via donau (2007). As it can be seen, the upstream direction requires much more energy since the vessel is sailing against the current and therefore emissions are higher. This fact is sometimes neglected by the assumption that vessels are usually sailing in both directions and therefore only average values for both directions are used. Although this might be true from the point of view of the vessel operator, the differences are important for single trips in intermodal planning.

### 3.4. Transshipment emissions

The transshipment operations in terminals also contribute to the overall CO<sub>2</sub>e emissions needed in a specific transportation chain. The amount of emissions released in a certain terminal depends on the infrastructure and the handling equipment used for the movement of containers. As Geerlings and van Duin (2011) show in the example of the port of Rotterdam, on its way from the sea ship to the hinterland transportation mode the container has to go through various operations in the terminal within which it is transported by different vehicles. The total energy in form of electricity or diesel needed for the movement of these vehicles was estimated to 18.25 kilowatt hours/transshipment from sea ship to rail which is also the value used in this paper for sea ports. In case of smaller inland terminals the factor of 4.4 kilowatt hours/transfer of one container is applied as recommended by IFEU (2011).

## 4. Modelling the green intermodal transportation

We now present a bi-objective linear mixed-integer mathematical formulation of the green intermodal service network design problem based on the formulation of Demir et al. (2016). We note that time-related costs are not considered in the model. The presented model combines economic and environmental objectives which will be optimised using different multi-objective optimisation approaches described in Section 4.1.

The objective of this model is to generate an optimal plan for orders  $p \in \mathcal{P}$  defined by their demand  $d^p$ , origin  $i$  and destination  $j$  nodes as well as earliest release  $\Gamma_{\text{release}}^p$  and due time  $\Gamma_{\text{duetime}}^p$ . Moreover,  $\gamma^p(i, j) = \{(p \in \mathcal{P}) | i \in \mathcal{N}^+ \text{ and } j \in \mathcal{N}^-\}$

Table 2. Sets and parameters.

Notation	Formal description
$\mathcal{N}$	Set of all transshipment locations
$\mathcal{N}^+$	Set of start terminals of transportation orders
$\mathcal{N}^-$	Set of end terminals of transportation orders
$\mathcal{P}$	Set of transportation orders
$\mathcal{S}$	Set of transportation services
$\Gamma_{\text{release}}^p$	Earliest release time of order $p$
$\Gamma_{\text{duetime}}^p$	Due time of order $p$
$c_j$	Transshipment costs per container in terminal $j$
$c^s$	Transportation costs per container of a service $s$
$c_{\text{emi}}$	Emissions-related costs per kg of CO <sub>2</sub> e emissions
$\text{cap}^s$	Free capacities of services $s$
$d^p$	Demand (in containers) of order $p$
$e_j$	Emissions in kg per transshipment of container in terminal $j$
$e^s$	Emissions in kg per transportation of container on service $s$
$L$	Large (enough) number
$t_j$	Separate loading and unloading time at terminal $j$
$t^s$	Transportation time of service $s$
$T_{\text{min}}^s$	Start of the departure time window for service $s$
$T_{\text{max}}^s$	End of the departure time window for service $s$

Table 3. Decision variables.

Notation	Formal description
$A^s$	Arrival time of service $s$ at the associated destination node
$D^s$	Departure time of service $s$ at the associated departure node
$l^{qr}$	A binary variable equal to 0 if transshipment is necessary between preceding services $q$ and succeeding service $r$ , 1 otherwise
$n_j$	The number of containers transhipped at terminal $j$
$y^s, y^{sp}$	A binary variable equal to 1 if service $s$ is used (for order $p$ )
$x^{sp}$	The number of containers of order $p$ carried via service $s$
$z^{qrp}$	The number of containers of order $p$ that have to be transhipped between preceding services $q$ and succeeding service $r$

is a set of orders with origin  $i$  and destination node  $j$ .  $\mathcal{N}^+$  and  $\mathcal{N}^-$  represent the set of start and end terminals of transportation orders, respectively. The orders can be routed in a transportation network consisting of services  $s \in \mathcal{S}$  (scheduled transports) and nodes  $i, j \in \mathcal{N}$  (transshipment locations). Each service, since it is connected to a schedule and vehicle, is unique and connects transshipment locations  $i$  and  $j$ . Therefore,  $\delta^s(i, j, D^s) = \{(s \in \mathcal{S}) | i \in \mathcal{N} \text{ and } j \in \mathcal{N}\}$  and is a set of services between origin  $i$  and destination node  $j$  within the starting time window bounded by  $T_{\text{min}}^s$  and  $T_{\text{max}}^s$ . In addition to that, services are characterised by their scheduled departure time  $D^s$  and service travel time  $t^s$  as well as service slot price  $c^s$  and CO<sub>2</sub>e emissions per container  $e^s$ . Services on the road as well as transshipments are assumed to be available when needed. We list all sets and parameters in Table 2 and decision variables in Table 3.

Using the notations described in Tables 2 and 3, we now provide the bi-objective mathematical formulation of the green intermodal service network design problem.

$$\text{minimize } f_1(x) = \sum_{p \in \mathcal{P}} \sum_{s \in \mathcal{S}} x^{sp} c^s + \sum_{j \in \mathcal{N}} n_j c_j, \quad (1)$$

$$\text{minimize } f_2(x) = c_{\text{emi}} \left( \sum_{p \in \mathcal{P}} \sum_{s \in \mathcal{S}} x^{sp} e^s + \sum_{j \in \mathcal{N}} n_j e_j \right), \quad (2)$$

subject to:

$$\sum_{s \in \delta(s \in \mathcal{S} | n=i)} x^{sp} = d^p \quad \forall n \in \mathcal{N} | n=i, p \in \mathcal{P} \quad (3)$$

$$\sum_{s \in \delta(s \in \mathcal{S} | n=j)} x^{sp} = d^p \quad \forall n \in \mathcal{N} | n=j, p \in \mathcal{P} \quad (4)$$

$$\sum_{s \in \delta(s \in \mathcal{S} | n=i)} x^{sp} - \sum_{s \in \delta(s \in \mathcal{S} | n=j)} x^{sp} = 0 \quad \forall n \in \mathcal{N} | (n \neq i, j), p \in \mathcal{P} \quad (5)$$

$$\sum_{p \in \gamma(p \in \mathcal{P})} x^{sp} - y^s cap^s \leq 0 \quad \forall s \in \delta(s \in \mathcal{S}) \quad (6)$$

$$x^{sp} \leq y^{sp} L \quad \forall s \in \delta(s \in \mathcal{S}), p \in \gamma(p \in \mathcal{P}) \quad (7)$$

$$x^{sp} \geq y^{sp} \quad \forall s \in \delta(s \in \mathcal{S}), p \in \gamma(p \in \mathcal{P}) \quad (8)$$

$$y^s \leq \sum_{p \in \gamma(p \in \mathcal{P})} x^{sp} \quad \forall s \in \delta(s \in \mathcal{S}) \quad (9)$$

$$\sum_{p \in \mathcal{P}} \sum_{\delta(s \in \mathcal{S} | i=n, j=n)} x^{sp} - 2 \sum_{p \in \mathcal{P}} \sum_{\delta(q \in \mathcal{S} | i=n)} \sum_{\delta(r \in \mathcal{S} | j=n)} z^{qrp} = n_n \quad \forall n \in \mathcal{N} \quad (10)$$

$$D^s + t^s - A^s \leq L(1 - y^s) \quad \forall s \in \delta(s \in \mathcal{S}) \quad (11)$$

$$A^q + t_j x^{qp} + t_j x^{rp} - 2t_j z^{qrp} - D^r - L(1 - y^{qp}) \leq L(1 - y^{rp}) \quad \forall q \in \delta(s \in \mathcal{S} | j \in \mathcal{N}), p \in \mathcal{P}, r \in \delta(s \in \mathcal{S} | i \in \mathcal{N}) \quad (12)$$

$$z^{qrp} \leq L l^{qr} \quad \forall q \in \delta(s \in \mathcal{S} | j \in \mathcal{N}), p \in \mathcal{P}, r \in \delta(s \in \mathcal{S} | i \in \mathcal{N}) \quad (13)$$

$$D^s - y^{sp} \Gamma_{\text{release}}^p \geq 0 \quad \forall p \in \mathcal{P}, s \in \delta(s \in \mathcal{S} | i \in \mathcal{N}^+) \quad (14)$$

$$A^s - \Gamma_{\text{duetime}}^p \leq L(1 - y^{sp}) \quad \forall p \in \mathcal{P}, s \in \delta(s \in \mathcal{S} | i \in \mathcal{N}^-) \quad (15)$$

$$T_{\min}^s y^s \leq D^s \leq T_{\max}^s y^s \quad \forall s \in \mathcal{S} \quad (16)$$

$$y^s, y^{sp} \in \{0, 1\} \quad \forall s \in \mathcal{S}, q \in \mathcal{S}, r \in \mathcal{S}, p \in \mathcal{P} \quad (17)$$

$$x^{sp}, z^{qrp}, D^s, A^s, AD^p \geq 0 \quad \forall s \in \mathcal{S}, q \in \mathcal{S}, r \in \mathcal{S}, p \in \mathcal{P}. \quad (18)$$

Equation (1) minimises the total transportation costs. The total transportation costs consist of transportation costs per container and service as well as the transshipment costs per container. In addition to that, CO<sub>2</sub>e emissions-related costs are included in Equation (2) consisting of emissions from transportation and transshipment of the container multiplied by the emission costs. Constraints (3)–(5) handle the movement of containers. While constraints (3) and (4) focus on the origin and destination nodes, constraint (5) manages the transshipment. Demand, in that regard, is positive if more containers are planned to originate from a specific node than are destined for that node. Constraint (6) ensures that capacity limits of services are adhered to. Constraints (7)–(9) make sure that a service is only allowed to process any amount of containers when it is selected. While (10) tracks the transshipment necessary, constraints (11) and (12) ensure the timely sequencing of the services within the network. As seen in (11), each service has interrelated departure, service and arrival times. In addition to the synchronisation at nodes in terms of loading units ((3)–(5)), constraint (12) takes care of the timely synchronisation. It ensures the relation of sequential services at a transshipment location. This is necessary due to more or less fixed schedules of services, which permit services with earlier departure times than possible preceding services from following up on them. Constraint (13) ensures that only containers which have to change the vehicle are considered when calculating transshipment times, costs and CO<sub>2</sub>e emissions. Constraints (14) and (15) provide the time frame for each order to plan within. Constraint (16) gives the time window within which services can depart with  $T_{\min}^s = T_{\max}^s$  being valid for scheduled services. The domain of the decision variables is given in constraints (17) and (18).

Since the model is an extension of the standard service network design problem, it is a non-deterministic polynomial time (NP)-hard problem. The complexity of the model based on its input is  $O(|S||P|)$  if  $|S||P| \geq |N||P|$  and  $O(|N||P|)$  if  $|S||P| \leq |N||P|$ . Considering the explosion in complexity along with the increase in instance size, advanced solution methodologies such as metaheuristic algorithm are needed to solve large-sized SND instances.

#### 4.1. The bi-objective optimisation

Multi-objective optimisation is the process of simultaneously optimising two or more conflicting objectives subject to a number of constraints. In this section, we consider a bi-objective problem of the form

$$\text{(MOO) minimise } \{f_1(x), f_2(x)\} \quad (19)$$

$$\text{subject to } x \in \mathcal{S}, \quad (20)$$

where  $f_k: \mathcal{R}^n \rightarrow \mathcal{R}$  are  $k=2$  objective functions to be minimised simultaneously. The decision variables  $x = (x_1, \dots, x_n)^T$  belong to a feasible region (set)  $\mathcal{S} \subseteq \mathcal{R}^n$ .

For non-trivial multi-objective problems, one cannot identify a single solution that simultaneously optimises every objective. While searching for solutions, one reaches a point such that, when attempting to improve an objective, other objectives suffer as a result. A solution is called Pareto optimal if it cannot be eliminated from consideration by replacing it with another solution which improves upon one of the objectives without worsening another. Finding Pareto solutions, and quantifying the trade-offs in satisfying the different objectives, is the goal of setting up and solving a MOO problem. Interested readers are referred to Demir, Bektaş, and Laporte (2014a) for more discussion on multi-objective optimisation models. We now describe multi-objective methods used in this paper.

##### 4.1.1. The basic weighting method (WM)

This method links each objective function with a weighting coefficient and minimises the weighted sum of the objectives. We assume that the weighting coefficients  $w_i$  are non-negative for all  $i=1,2$ . Weights are normalised in such a way that  $\sum_{i=1}^2 w_i = 1$ . The problem is then transformed into the following problem:

$$\text{minimise } w_1 f_1(x) + w_2 f_2(x) \quad (21)$$

$$\text{subject to } x \in \mathcal{S}. \quad (22)$$

This problem (21)–(22) can be solved by linear programming methods.

##### 4.1.2. The weighting method with normalisation (WMN)

This is an extension to the previous method where the objective functions are normalised to take values between 0 and 1 (Grodzevich and Romanko 2006). This is done by using the differences of optimal function values in the worst and the best solutions. The problem is transformed into the following problem:

$$\text{minimise } w_1 (f_1(x) - z_1^U) / (z_1^N - z_1^U) + w_2 (f_2(x) - z_2^U) / (z_2^N - z_2^U) \quad (23)$$

$$\text{subject to } x \in \mathcal{S}, \quad (24)$$

where  $z^U$  is the Utopian solution, and  $z^N$  is the Nadir solution. The Utopian solution can be calculated as  $z_i^U = f_i(x^{[i]})$  where  $z_i = \arg \min_x \{f_i(x) : x \in \mathcal{S}\}$ . The Nadir solution may be feasible and provides upper bounds for the Pareto optimal set. It is calculated as  $z_i^N = \max_{1 \leq j \leq k} f_i(x^{[j]})$ ,  $\forall i = 1, \dots, k$ . We calculate these solutions by calculating the best and the worst values of each objective function.

##### 4.1.3. The $\epsilon$ -constraint method (ECM)

One of the objective functions is selected to be optimised, while all others are converted into constraints by imposing an upper bound. The problem to be solved then takes the form

$$\text{minimise } f_l(x) \quad (25)$$

$$\text{subject to } f_j(x) \leq \epsilon_j \forall j, l = 1, 2; \quad j \neq l \quad (26)$$

$$x \in \mathcal{S}. \quad (27)$$

The right-hand side of constraint (26) is gradually increased by a small amount and the problem is solved again whenever  $\epsilon_j$  is increased. The weighting method might lead to an extreme solution. In contrast, the  $\epsilon$ -constraint method is able to produce non-extreme solutions. Moreover, the computational effort is less than that of the weighting method.

## 5. Case study: Intermodal transportation of goods to Hamburg

As already described in Section 1, the planning complexity and high number of involved actors might be some of the reasons for a low share of intermodal transportation on modal split, especially when it comes to transportation of goods on relatively short distances (Hanssen and Jorgensen 2012). However, intermodal solutions are very often used for long-distance overseas transportation where goods are carried in containers by sea vessels between ports and the hinterland transportation between the respective port and the origin or destination is carried out by other transportation modes, e.g. truck, train or inland vessel. In order to reflect this development, the presented bi-objective green intermodal problem has been tested on a case study analysing possible routes for exporting containerised goods via the port of Hamburg.

The hinterland transportation flows of the port of Hamburg are divided between rail (42%), road (56%) and inland waterway (2%) (Port of Hamburg 2017), which means that all three transportation modes used in intracontinental transportation are represented. The high share of rail can be achieved due to an extensive network of regular rail services connecting various terminals in Western and Central Europe. The low share of IWT can be explained by the fact that Hamburg is connected to other ports only via the river Elbe with rather low transportation volumes. Nevertheless, the combination of intermodal services bringing goods to this port is a good basis for comparing the effect of different objectives and optimisation methods as it is shown in this case.

In order to design the case study, 29 different inland terminals, from which the port of Hamburg can be reached, have been chosen. These terminals are located in Germany, Austria, Czech Republic, Slovakia and Hungary and are summarised in Figure 6 and Table 4.

As it can be observed, all of the considered terminals combine at least two transportation modes, whereby one of them is almost in all cases road and the other one is mostly rail, with the exception of Magdeburg, Riesa, Regensburg and Linz, where road is combined with IWT. The only terminal where road transportation is not considered is Duisburg, since here extensive number of rail services and also IWT services are available. Besides the 26 bimodal terminals, four of the terminals, namely Hamburg, Nuremberg, Vienna and Budapest, combine all three modes. The reason for the low number of trimodal terminals is mainly the limited availability of IWT services, which are restricted by available rivers and were therefore considered only for connections between Hamburg and terminals located on the river Elbe (i.e. Magdeburg, Riesa) and for terminals on the river Danube (i.e. Budapest, Vienna, Linz, Regensburg, Nuremberg, Duisburg).

The considered terminals are connected by intermodal transportation services as it is presented in Table 4. Besides the IWT services between the ports on the considered rivers, the majority of connections is served by rail services that are based on publicly available container train schedules (e.g. HUPAC 2017; Kombiverkehr 2017; Metrans 2017). In addition to that, selected road services have been added to the network in order to increase the number of alternative routes and add connections which are not usually served by train. As a result, all terminals have a direct connection to Hamburg by at least one transportation mode, but are also connected to other terminals in order to enable the combination of different services if this option is more advantageous than the direct transport.

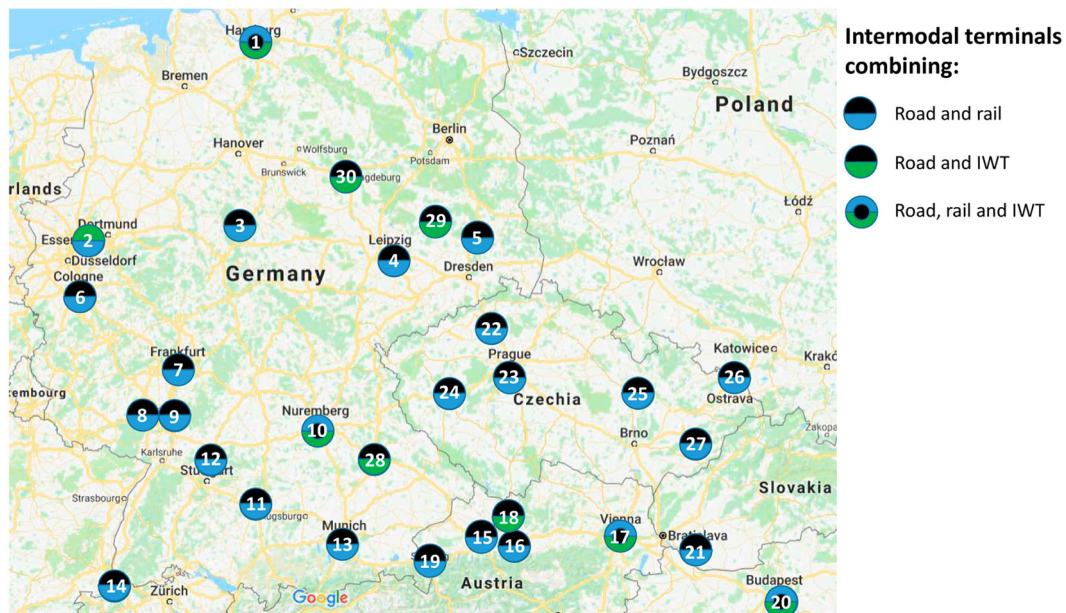


Figure 6. Terminals in the transportation network.

Table 4. Intermodal freight transportation instance.

Terminal no	Terminal name	Road	Rail	IWT	Connecting services by		
					Road to terminals	Rail to terminals	IWT to terminals
1	Hamburg	x	x	x			
2	Duisburg		x	x		1, 4, 8, 13, 15, 17, 20, 22, 23	10
3	Göttingen	x	x		7, 14, 16, 23, 28, 30	1	
4	Leipzig	x	x		10, 19, 23, 29	1, 2, 5, 13	
5	Schwarzheide	x	x		15, 22, 30	1	
6	Cologne	x	x		21	1, 11, 12, 13, 14	
7	Frankfurt	x	x		3, 9, 12, 14, 16	1	
8	Ludwigshafen	x	x		9	1, 2, 13, 15	
9	Mannheim	x	x		7, 8, 10, 24	1	
10	Nuremberg	x	x	x	4, 9, 11, 23, 27	1, 13	2,28
11	Ulm	x	x		10, 12, 13, 28	1, 6	
12	Kornwestheim	x	x		7, 11, 14	1, 6	
13	Munich	x	x		11, 16, 19, 20	1,2,4,6,8,10	
14	Basel	x	x		3, 7, 12, 19	1, 6	
15	Wels	x	x		1, 5, 19, 26	2, 8, 17, 20	
16	Enns	x	x		3, 7, 13, 17, 18, 25	1	
17	Vienna	x	x	x	16, 21	1, 2, 15, 25	18, 20
18	Linz	x		x	1, 16, 23, 30		17, 28
19	Salzburg	x	x		1, 4, 13, 14, 15	23	
20	Budapest	x	x	x	26	1, 2, 13, 15, 17, 21	17
21	Dunajska Streda	x	x		1, 6, 17, 22	20, 25	
22	Lovosice	x	x		5, 21, 24, 27	1, 2	
23	Prague	x	x		1, 3, 10, 18	2, 4, 19, 24, 25	
24	Plzen	x	x		1, 9, 22, 29	23	
25	Ceska Trebova	x	x		1, 16	17, 21, 23, 26, 27	
26	Ostrava	x	x		1, 5, 15, 20	25	
27	Zlin	x	x		1, 10, 22	25	
28	Regensburg	x		x	1, 3, 11		10, 18
29	Magdeburg	x		x	1, 4, 24		1, 30
30	Riesa	x		x	1, 3, 5, 18		29

As it can be seen in Table 4, most of the German terminals are connected to Hamburg by rail services, whereas the Czech terminals only have road services available. This is caused by the fact that a lot of rail feeder services are available in the Czech Republic, Slovakia and Hungary, which only deliver the goods to the bigger terminals (e.g. Prague, Ceska Trebova, Budapest), where the transportation volumes are then consolidated and sent by one train to other terminals in Western Europe (e.g. Vienna, Munich, Duisburg, Hamburg). For Hamburg, no outgoing connecting services have been considered since the case study is concentrated on the export of goods from Europe via Hamburg and therefore only inflows to Hamburg are important. The connections are served by multiple services per week which increases the number of possible transportation plans. In total, 30 terminals are served by 400 services.

The considered services are characterised by their origin, destination, distance, capacity, departure time, travel time, transportation costs and CO<sub>2</sub>e emissions per transported container (TEU). Thereby, these characteristics differ between the transportation modes but also between the individual services. Whereas the rail and IWT services depart according to a certain schedule, road services can be used when they are needed, since they are usually more flexible. The transportation costs were estimated as costs needed to transport one TEU without considering pricing policies of logistics service providers and are dependent on different factors including transportation mode, distance, speed and travel time, tolls and infrastructure charges, capacity and utilisation of the vehicle as well as departure time, since e.g. travel times of trains might differ due to limited availability of time slots during different times of a day.

The calculation of costs is based on PLANCO (2007), PTV (2017) and via donau (2007), whereby the cost factors are between 0.6–0.8 EUR/TEU-km for road, 0.2–0.6 EUR/TEU-km for rail and 0.2–0.4 EUR/TEU-km for IWT services. The calculation of CO<sub>2</sub>e emissions for each service is based on the methods presented in detail in Section 3. Since it was shown there that the relationship between total emissions and the utilisation of the vehicle is non-linear for rail and IWT, a utilisation of 80% was assumed for trains (PLANCO 2007) and 90% for vessels (via donau 2006) in order to be able to use the linear optimisation model. In addition to that, it was assumed that almost all rail services are operated by electric trains. The only exception are trains starting and ending at terminal 21 in Dunajska Streda, since the track there is not electrified. As

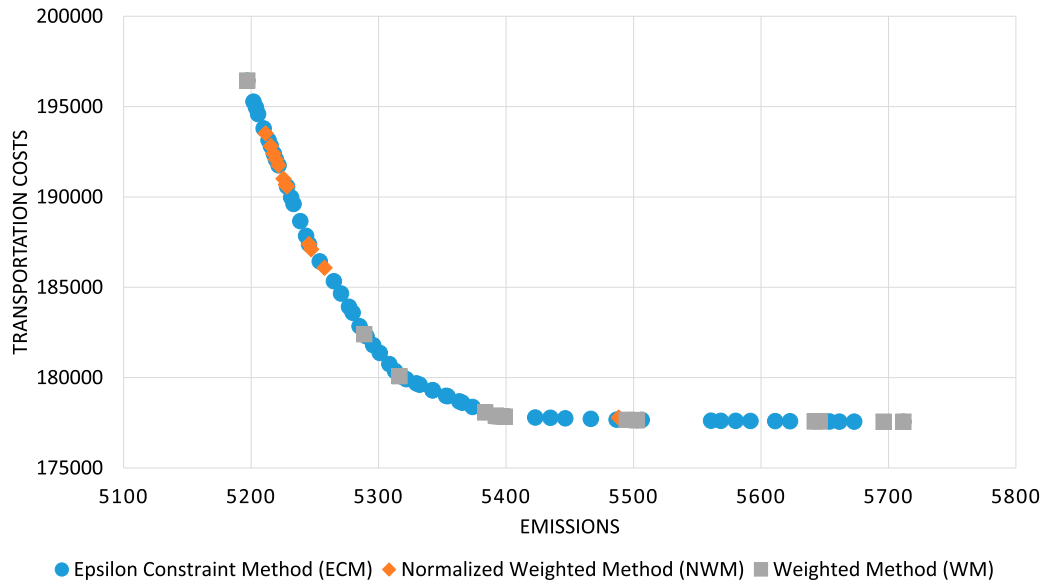


Figure 7. All Pareto solutions.

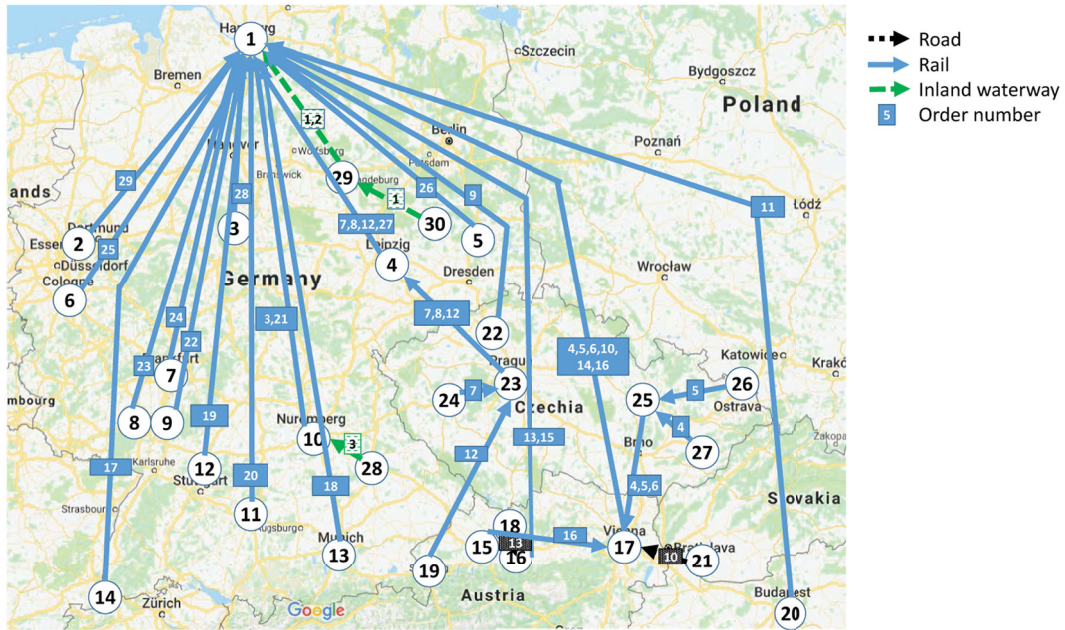
a result, around 0.6 kg of CO<sub>2</sub>e emissions are needed per TEU-km in case of road, 0.05–0.25 kg of CO<sub>2</sub>e emissions/TEU-km were assumed for electric trains depending on the electricity mix of each country where the service is operated in, ca. 0.25 kg of CO<sub>2</sub>e emissions/TEU-km are needed for diesel trains, and for IWT services 0.15–0.20 kg of CO<sub>2</sub>e emissions/TEU-km are released for sailing downstream and 0.30–0.45 kg of CO<sub>2</sub>e emissions/TEU-km are released when sailing upstream. The emission costs were assumed to be 70 EUR/ton (PLANCO 2007).

The described services can be used to find the optimal plans for multiple transportation orders received from customers. In total, 29 orders were considered for planning, whereby one order was sent from each inland terminal to Hamburg. Each order is characterised by its origin, destination, the number of TEU that have to be transported and its release and delivery time window. Thereby only containerised goods in general were considered and an average weight of 14 ton/TEU was assumed. The number of containers per order was randomly chosen between one and 35 and the planning horizon for delivering the orders was one week. The release time for containers was again random within the first three days of the planning horizon, which means that the time windows between release and delivery times were between four and seven days.

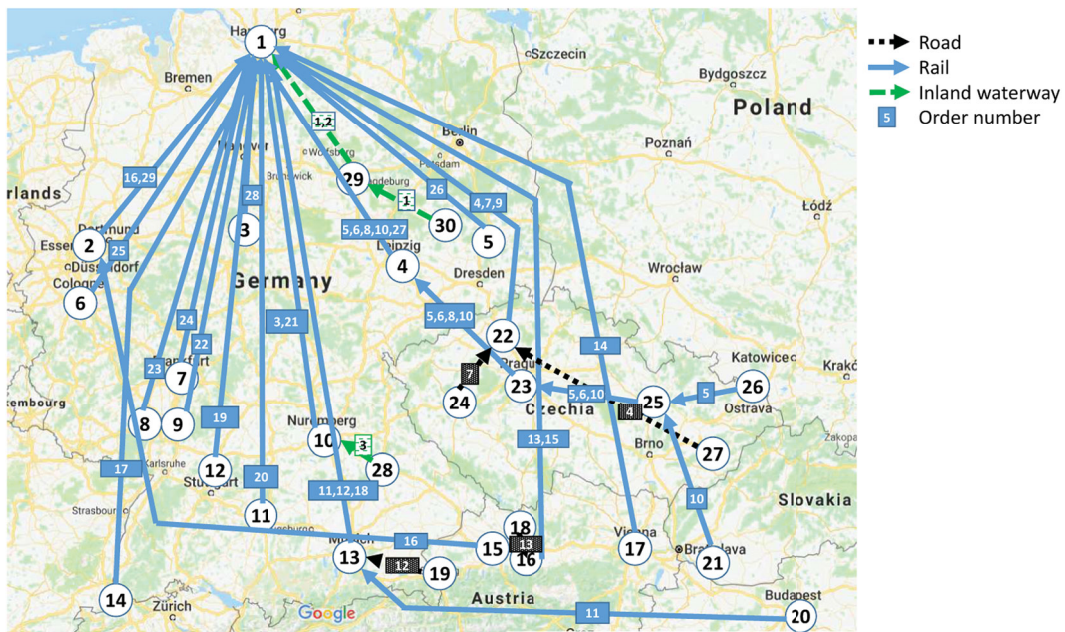
The optimal routes were calculated using IBM CPLEX 1271 for the three bi-objective methods presented in Section 4.1 in order to be able to compare their performance. Each bi-objective model was run for 500 times to obtain non-nominated solutions. More specifically, the weights of WM were adjusted 500 times each ranging between zero and one and totalling exactly the value of one. The weights of WMN were normalised using the Utopian and Nadir solutions which were also obtained using the mathematical model. After finding these points, weights were updated as it was done in the WM. For the ECM, the best solution for each objective function was found separately and these solution values used as constraints in the model. The right-hand side value of the constraint was increased each time slightly to obtain Pareto solutions.

The performance assessment of techniques in multi-objective optimisation is less straightforward than in single objective optimisation. The output of multi-objective optimisation is a set of solutions approximating the Pareto optimal front as discussed in Zitzler et al. (2003). In our analysis, we use the hypervolume indicator and the number of Pareto solutions found as an additional way of assessing performance. The hypervolume indicator metric computes the volume of a given solution region. In other words, the hypervolume indicator is the area of the union of all rectangles. The larger the value of the indicator (area), the better is the set of solutions. The Pareto solutions found with each method are shown in Figure 7.

As it can be seen from Figure 7, WM provided 15 Pareto solutions located mainly in the area where costs are minimised since the emission costs are too low in comparison to transportation costs and therefore the emission-minimising solutions are only obtained for very high emission weights. WMN provided 17 Pareto solutions showing mainly the different possible solutions close to the area where emissions are minimised. The ECM method provided the highest number of 55 Pareto solutions. We note that the ECM obtained more Pareto solutions because it has better coverage for both objectives. Especially, in our case solution values differ drastically (i.e., costs are minimum 175,000 and emissions are minimum 5100). Since the difference is huge, ECM is expected to give better results even though we normalise the weights in weighting method. According to the hypervolume indicator, ECM is superior to the other two methods. In other words, the solutions



(a)



(b)

Figure 8. Comparison of costs-minimising and emissions-minimising solutions. (a) CO<sub>2</sub>e emissions-minimising solution. (b) Transportation costs-minimising solution.

found by ECM represents a larger area than the other methods. WMN has 2.2% large area compared to WM and ECM has 2.5% large area compared to WMN.

When looking at the results in detail, it can be observed that most of the optimal routes, especially from the German terminals, use direct train connection to the port of Hamburg. However, there are many terminals located especially in Austria and Czech Republic which only have a truck connection with Hamburg or the train connection is not convenient and therefore multiple services are combined in the optimal route. The inland waterway services are used for orders departing from the ports located on the river Elbe, whereas Danube is used only very rarely since it has no direct connection to the



Table 5. Changes in order routes between costs-minimising and CO<sub>2</sub>e-minimising solution.

Order no.	CO <sub>2</sub> e emissions-minimising solution		Costs-minimising solution		Difference in costs in %	Difference in CO <sub>2</sub> e emissions in %		
	Route	Costs in EUR per TEU	CO <sub>2</sub> e emissions in kg per TEU	Route			Costs in EUR per TEU	CO <sub>2</sub> e emissions in kg per TEU
4	27-25-17-1	758.00	213.37	27-22-1	577.00	332.53	- 23.88	55.85
5	26-25-17-1	757.00	230.37	26-25-23-4-1	591.00	234.59	- 21.92	1.83
6	25-17-1	622.00	186.37	25-23-4-1	456.00	194.59	- 26.68	4.40
7	24-23-4-1	491.00	171.59	24-22-1	414.00	208.53	- 15.68	21.53
10	21-17-1	617.00	213.00	21-25-23-4-1	616.00	268.22	- 0.00	25.92
11	20-1	556.50	196.33	20-13-1	502.50	205.39	-9.70	4.61
12	19-23-4-1	480.00	193.51	19-13-1	420.00	214.51	- 12.50	10.85
16	15-17-1	624.00	162.29	15-2-1	345.00	184.51	- 44.71	13.69

destination port. The rail services are prevailing whereas road services have rather lower share depending on the weights used for the solution.

The changes in optimal routes are mainly visible when the two extreme solutions, namely the costs-minimising solution and the CO<sub>2</sub>e emissions-minimising solution are compared as it can be seen in Figure 8.

In this figure, the optimal routes for each order are shown whereby orders are numbered in the opposite direction to their origin, starting with order 1 departing from node 30 up to order 29 departing from node 2. Whereas the emissions-minimising solution favors the bundling of the orders on the direct train from Vienna to Hamburg due to lower electricity emission factors in Austria and Germany, in the cost-optimising solution truck services are used to deliver the containers to the terminal of Lovosice where a direct train to Hamburg starts. In total, moving from the costs-minimising solution to the emissions-minimising solution leads to an increase in total transportation costs by 10.6% whereas 9.1% of emissions can be saved. However, the Pareto frontier in Figure 7 shows that almost 6% of the total CO<sub>2</sub>e emissions can be saved when an increase in total transportation costs of 0.5% is allowed. This can be achieved by redirecting the orders 5 and 6 via Prague and orders 11 and 12 via Munich.

The changes in plans can have several reasons, as it is also illustrated in Table 5, where all changed orders from Figure 8 are summarised. When the routes are optimised according to CO<sub>2</sub>e emissions, orders 5, 6 and 10 are routed via Vienna (terminal 17) instead of using Prague (terminal 23) as the shortest route. The reason for this is the high emission factor for Czech Republic where a substantial part of electricity is produced by burning coal and also one additional transshipment needed if the route via Prague is chosen. However, whereas the differences in emissions are not very high, differences in costs are substantial and therefore the route via Prague and Leipzig is chosen in the costs-minimising solution. In addition to that, it can be also observed that the relatively short rail connections between terminals 23, 25, 26 and 27 within the Czech Republic are expensive in comparison to direct truck transportation and therefore orders 4 and 7 use truck transportation to terminal 22 and a direct train service to Hamburg if costs are minimised. This would be probably valid also for orders 5 and 6, however, truck services from terminals 25 and 26 were not considered in the case study design. In case of order 11, the direct service from Budapest to Hamburg was assumed to drive via Slovakia and Czech Republic where the infrastructure charges are quite high. Moreover, the travel time according to the schedule is quite long with 24 hours which further increases the calculated costs. On the other hand, CO<sub>2</sub>e emissions are slightly lower due to shorter distance. Therefore, the direct service between Budapest and Hamburg is chosen for emissions optimisation and the connection via Munich is chosen for costs optimisation. For order 12, the preference of the emissions optimising solution is to choose connection via Czech Republic which only includes electric trains, whereas the cost optimal solution suggests that it might be better to accept a truck service from Salzburg to Munich since this option is cheaper. Last but not least, in case of order 16 the connection via Vienna minimises the CO<sub>2</sub>e emissions, but since the travel time of the service from Vienna to Hamburg is very long, the cost optimal solution suggests to use faster trains and go via Duisburg.

As the described case study shows, incorporating of some of the factors from the green logistics approach defined in Table 1 into planning can positively influence the results. The simultaneous planning of multiple orders and consideration of the whole transportation network helps to find the global optimum and resolve potential problems with limited capacity if too many orders are consolidated on one service. The calculation of costs and CO<sub>2</sub>e emissions for the individual services was based on multiple data sources and input factors so that differences between services based on their travel time and route could be identified, which also influenced the final results as it is described in the previous paragraph. This is not possible if only single data source such as distance would be taken into account. From the mode perspective, three different modes were considered in the planning process which enabled to highlight their advantages and to find their best combination for the global optimum. The bi-objective optimisation also showed the trade-off between economic and ecological factors and their influence on the resulting route. Since the case study was concentrated on finding the optimal plans for multiple

transport orders, the focus was put on offline planning which allows to search for different alternatives and compare them in contrast to online planning where the objective is to find a plan as fast as possible during transport execution. Moreover, the data inputs were rather deterministic in order to reduce the complexity of the model which increases when stochastic factors are added.

## 6. Conclusions and future research directions

Many transportation and route planning tools are available in the market but very often they are based on traditional approach while the consideration of green logistics approach is only limited. By using the models and algorithms introduced in green logistics literature, new functionalities, for example, can help reducing the number of empty miles that is driven, improve the modal split, and reduce transportation times, as well as response times to unexpected events during transportation.

This paper has focused on the principles of green logistics and different possibilities of incorporating the environmental factors into transportation planning since this topic is gaining importance. Despite this fact, the current TMS software packages still use relatively simple models to minimise the amount of CO<sub>2</sub>e emissions emitted or do not consider environmental impacts at all. New directions discussed in this paper could be easily integrated with such software packages to take into account CO<sub>2</sub>e emissions for a real implementation in practice. This is an important development for at least two reasons: (i) the integration of the algorithms introduced in the literature and TMS software could save money, time and energy, (ii) the interactive selection from a set of Pareto solutions generated by the algorithms would allow for flexibility, productivity and support for planners of transportation companies. The results of the case study also confirm that green approach yields good-quality solutions in terms of both of these reasons.

The consideration of environmental aspects together with the traditional cost optimisation approach leads to conflicting situations in terms of finding the optimal solution for both economic and environmental objectives. As the comparison of different bi-objective optimisation approaches showed, the  $\epsilon$ -constraint method offers in this case a variety of different solutions showing the Pareto optimal solutions over the whole region between the cost-minimising and the emissions-minimising solution. The results also highlighted the fact that it is possible to achieve a substantial reduction in one objective (e.g. emissions) when a small increase in the other objective (e.g. costs) is allowed. Therefore, the integration of multi-objective approaches into TMS tools could offer various alternatives to the planners who could then choose routes which improve the environmental factor at a low increase in the cost factor.

One of the limitations of this study is that the mathematical optimisation is not capable of solving large-sized instances due to the problem complexity. This limits to see the trade-offs on practical large-sized networks. Another limitation of this study is to exclude other negative externalities of transportation. Since green logistics include other environmental concerns, the current research could also look at air pollution, noise and accidents as well.

Considering the development of the intermodal transportation, the following two areas were identified as further research directions, which include: (i) developing metaheuristic algorithm to solve large-sized multi-objective instances to simultaneously consider three objectives, including transportation time, transportation costs and emissions, and (ii) developing an integrated simulation and optimisation tool with more advanced multi-objective optimisation algorithms and techniques to investigate the major negative externalities of intermodal transportation.

## Acknowledgements

We would like to thank the four reviewers for their detailed comments and suggestions for the paper.

## Disclosure statement

No potential conflict of interest was reported by the authors.

## Funding

The authors gratefully acknowledge funding provided by Cardiff University, by WU Vienna University of Economics and Business and by Eindhoven University of Technology.

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