Proceedings of the 2023 Winter Simulation Conference
C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

INTEGRATING A MODE CHOICE MODEL INTO AGENT-BASED SIMULATION FOR FREIGHT TRANSPORT PLANNING AND DECARBONIZATION ANALYSIS

Senlei Wang
Dhanan Sarwo Utomo
Philip Greening

Center for Sustainable Road Freight
Heriot-Watt University
The Avenue
Edinburgh, EH14 4AS, UK

ABSTRACT

This paper presents a framework for integrating a discrete mode choice model with agent-based simulation. The integrated framework provides a more realistic representation of long-haul freight transport and is applied to the real-world scenarios of moving freight from ports to inland destinations via road, rail, and inland waterways. It incorporates a mode choice component that captures demand shifts between modes in response to different policy and vehicle technology interventions. The objective is to investigate the financial and environmental impacts of introducing new vehicle technologies and associated energy sources under different future scenarios in a UK multimodal freight system.

1 INTRODUCTION

Climate change is one of the most pressing global challenges facing us today. Emissions of Greenhouse Gases (GHG) resulting from human activity are the primary driver of global warming. Transportation, which meets the movement needs of people and goods, is the most significant contributor to GHG emissions globally. GHG emissions from transportation primarily come from burning fossil fuels by different modes of transport (e.g., cars, trucks, trains, ships, and airplanes). In 2020, transportation was the largest emission sector in the UK; the entire transport sector accounts for about 24 % of the total UK GHG emissions. Emissions of moving freight using heavy goods vehicles (HGVs) and vans make up about 35 % of UK domestic transport GHG emissions (Department for Transport 2021). Road freight, the backbone of trade and commerce, will more than double by 2050 as economic activities increase. Road freight is, thus, a fast-growing GHG emitter (Haugen et al. 2022; Mulholland et al. 2018; Paddeu and Denby 2020).

As we are moving closer to the net-zero transition deadline by 2050, delivering effective decarbonization strategies for logistics systems is crucial to reducing GHG emissions and addressing climate change linked to freight activities. Mckinnon (2016) discussed the challenges and opportunities for decarbonizing freight transport, which involves implementing strategies to minimize the carbon footprint of freight transport operations. It argues that freight transport will face increasing pressure to decarbonize as global trade, economic development, and climate change adaptation create more demand for freight movement. Various decarbonization measures have been identified, such as using alternative fuels, optimizing delivery routes, transferring freight to greener transport modes, collaborating and sharing resources, improving energy efficiency, and enhancing vehicle loading. Achieving deep decarbonization of logistics by 2050 will require a combination of these measures and a strong political commitment to environmental objectives.

Shifting freight to lower carbon intensity modes can be an effective way to reduce the carbon emissions associated with logistics (Kaack et al. 2018; Nassar et al. 2023). For example, transporting goods by rail or inland waterway freight mode produces lower emissions than transporting them by road haulage. In addition to reducing carbon emissions, shifting freight to lower-carbon modes can also help reduce traffic congestion, improve air quality, and reduce transportation costs. However, the effectiveness of this strategy varies depending on factors such as the distance of the shipment and load factors. Furthermore, while rail and waterway transport have a lower environmental impact in transporting goods compared to trucking, road haulage remains the dominant freight mode due to the flexibility and convenience of its service characteristics.

There is a strong commitment to enhancing the environmental sustainability of freight transport across all modes. The application of new vehicle technologies has the potential to reduce the environmental impacts of all freight transport modes. Many technical advancements have been made to vehicle technologies. Improving the energy efficiency of vehicles, increasing vehicle carrying capacity, and switching to alternative fuels could be effective approaches to reducing the environmental impact of freight transport. Switching to low-carbon or zero-carbon alternative fuels can significantly reduce GHG emissions relative to conventional fossil fuels (Gómez Vilchez et al. 2022; Van Grinsven et al. 2021). The road freight industry has been undergoing rapid advancements in alternative fuel vehicle technologies. For example, heavy goods vehicles (HGV) can be powered via renewable electricity or green hydrogen. The application of these new vehicle technologies could significantly reduce emissions compared to conventional fossil fuel-powered vehicles.

This paper aims to develop an agent-based model (ABM) to assess the effectiveness of two strategies in decarbonizing an inland multimodal freight system that relies on road, rail, and inland waterway (IWW) transport. The first strategy involves the adoption of alternative fuel vehicle technologies (i.e., battery HGVs and Hydrogen-powered HGVs) in road freight transport. The second strategy considers the use of carbon pricing as a means of shifting freight to lower carbon intensity modes.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the model logic, while the data and experiments setup are given in Section 4. Section 5 provides a detailed discussion of the simulation results and compares the effectiveness of the two strategies for decarbonizing freight transport. The final section summarizes the main findings and suggests directions for future research.

2 LITERATURE REVIEW

In the freight system, the choice of transport mode can have a significant impact on the environment, and the environmental consequences of our transportation choices should be considered. Modal shift to more sustainable alternatives, such as rail and waterways with lower environmental impacts (emissions are several times less per tonne-km), is one of the most cost-effective ways of reducing transport emissions (Nicolet et al. 2022; Pearce and Zdemiroglu 2002). Modal shift could be driven by multiple factors. Kaack et al. (2018) examine the literature and data on road, rail, and IWW freight activities on the potential and barriers of shifting freight from road to low-carbon alternatives. They found that rail and IWW freight transport is much more efficient and less carbon-intensive than road freight, but most countries are experiencing growth in road freight. Policies, such as infrastructure investment in rail, internalizing external costs of road freights, and subsidies could promote modal shifts from road to low-carbon modes. Arencibia et al. (2015) estimated freight shipper preferences using data obtained from a stated preference (SP) survey and analyzed the relative importance of factors that could influence modal choices between road and rail in domestic freight transport. Important attributes of transport cost, transit time, punctuality, and service frequencies, are included in the stated-choice experiment. Regmi and Hanaoka (2015) developed a mode choice model using the data from an SP survey. The attributes of travel time, transport cost, and reliability are included in the SP experiment. They analyzed modal shifts from road to rail freight in a freight corridor and estimated the CO_2 emissions reduction from modal shift. Tao et al. (2017) analyzed the mode choice behavior of shippers between alternatives (i.e., road, combined road, rail, combined road, and IWW) and calculated mode shares using a random coefficient logit model. Using a bottom-up estimate of CO_2 emissions, reductions were observed because of modal shifts from road to combined road and rail transport induced by a subsidy policy in a container transport corridor. Yan et al. (2021) developed a freight transport modeling framework in which a discrete choice model is used to estimate mode shares and decide the types of alternative fuel vehicles based on the cost of transport modes and associated vehicle types. Energy and emissions are also projected with current and future scenarios. The potential of policy, vehicle technology, and infrastructure on the modal shares. Different criteria (both quantitative and qualitative) are considered in freight modal choice decisions. However, environmental criteria that might influence choice decisions are not included as mode choice variables. Emissions are important attributes for decision-makers (e.g., shippers). They will not only consider the transport cost and time as primary criteria but explicitly evaluate the cost of emitting carbons in their choice decision-making process. The current understanding of how emission costs impact transportation mode selection is limited, and there is a need to develop models that incorporate emissions as a factor (attribute) in decision-making.

Many existing freight models are originally developed for passenger transport, for example, the use of a four-step travel forecasting approach (with modifications) comprising trip generation, trip distribution, modal choice, and traffic assignments. In passenger transport, the integration of mode choice models in agent-based simulation has been widely investigated. These integrated models have been used to understand the behavior in response to various technology and policy interventions. MATSim is an agent-based transport simulation framework that integrates mode choice models to simulate the behavioral response of travelers for different future scenarios, including the introduction of carsharing systems and automated mobility-on-demand systems (Axhausen 2016; Hörl et al. 2021; Liu et al. 2017). Wang et al. (2022) developed an agent-based modeling framework using the Anylogic platform to simulate competition between multiple urban automated-mobility-on-demand operators. A mode choice component is implemented to capture the behavioral response to different prices (fares). SimMobility, with the implementation of behavioral models, investigates the impacts of emerging transportation services and infrastructures on people's travel and land use (Adnan et al. 2020; Azevedo et al. 2016; Basu et al. 2021; Gopalakrishnan et al. 2020; Nguyen-Phuoc et al. 2023; Zhu et al. 2018).

SimMobility urban freight transport modeling functionalities have been developed for evaluating logistics solutions at a disaggregate level associated with establishments, shipments, and goods vehicles (Le et al. 2016; Sakai et al. 2020). MASS-GT is an agent-based modeling framework for urban goods transport that could model logistical choices at individual levels (De Bok and Tavasszy 2018). The modeling framework has been applied to analyze the impacts of zero-emission vans in the Netherlands (de Bok et al. 2022). However, the application of these integrated models to long-haul freight transport has been limited due to unique characteristics of freight transport, such as shipment size and weight, mode and route selections, and energy consumption and emissions levels. To overcome the limitation, a framework is presented for integrating a discrete mode choice model with agent-based long-haul transportation simulation. The framework allows for the simulation of domestic long-haul freight transportation, including the choice of mode. The proposed framework considers the cost of emissions in the choice decision. This integration provides an approach to understanding how demand responds to different policies (e.g., carbon cost) and emerging vehicle technology interventions in future scenarios.

There has been significant development of alternative fuel and vehicle technologies (Gómez Vilchez et al. 2022). Hydrogen and electricity are key fuels of relevance for use in road freight. The use of battery HGVs and hydrogen-powered HGVs (whose electric motor is powered by fuel cells) with zero tailpipe emissions is being considered in business and policy decisions (Cantillo et al. 2022). These alternative fuel and vehicle technologies have the potential to provide benefits, including emission reductions and profitability for businesses. However, the magnitude of these benefits compared to the use of conventional diesel-powered HGVs in the current market application is uncertain. The carbon savings and profitability of using alternative fuel and vehicle technologies are important considerations for logistics service providers. To address the uncertainty, the developed ABM is used to estimate the carbon and cost impacts of using battery HGVs and hydrogen-powered HGVs in road freight and to describe the modal shift under different current and future scenarios with such vehicle technology interventions.

The main contributions are summarized as follows:

Firstly, a service attribute of GHG emissions is included in the model choice component. The model choice component is integrated into an agent-based framework for inland multimodal freight transport in which freight is transported via road, rail, and IWW transport.

Secondly, by incorporating a mode choice component, this paper conducts simulations to predict modal shift resulting from the adoption of battery and hydrogen HGV technology interventions in long-haul transportation applications. The analysis also examines how different carbon prices on the selection of freight modes with lower carbon intensity.

Thirdly, this paper estimates the cost and GHG emissions impacts of battery and hydrogen-powered HGVs in both current and future scenarios and compares these impacts to those of conventional vehicles.

3 MODE LOGIC

Agent-based modeling is an approach to modeling a complex system by describing its constituents (agents) and their interaction (Bonabeau 2002; MacAl and North 2010; Macal and North 2014). Each agent can make its own decisions to respond to changes in its environment or learn to improve its performance. These flexibilities make the agent-based approach suitable for modeling logistics systems in which multiple agents (e.g., shippers, carriers, and establishments) interact with each other and with the environment.

The developed modeling framework is able to simulate the movement of port freight to different inland destinations by road, rail, and IWW transport. The choice sets include three alternatives-road, rail, and inland waterways. The mode choices were modeled at an aggregate level. The multinomial logit model (MNL) allocates freight transport demand in an area over the available transport modes. The probability of choosing a specific alternative is calculated based on a multinomial logit model (see Equation (1)) (Samimi et al. 2011). The probability of choosing an alternative is assumed to increase monotonically with that

$$P_{mg} = \frac{e^{\mu G_{mg}}}{\sum_m e^{\mu G_{mg}}} \tag{1}$$

alternative's systematic utility.

To reflect the quantified disutility, the generalized cost in Equation (2) is used and mapped into the utility space as the systematic part of the utility. In this study, the generalized costs are the direct monetary costs of transporting goods, such as transport costs, as well as the influence of other qualitative characteristics of the modes, such as travel times and carbon emissions, expressed in monetary terms. Time is converted to a monetary value using a value of time, and a carbon price is factored in as a cost for emitting GHGs. This allows for the incorporation of the carbon cost component in the generalized cost function, explicitly assigning a price to GHG emissions and thereby reflecting the disutility of emissions.

$$G_{mg} = C_m + \alpha_g T_m + E_m + ASC \tag{2}$$

Where

G = generalized costs (Pounds/ton)
C = transport costs (Pounds /ton)
T = transport time (hour)
α = value of time (Pounds /ton*hour)
E=emission costs (Pounds/ton)
ASC=alternative specific constant

Factors that influence modal shift include transport cost, transport time, reliability, flexibility, service frequency, transshipments, and shipment attributes. The MNL model includes three attributes of modes: travel cost, travel time, and GHG emissions. Other explanatory factors have not been considered. The ASC is used to account for unobserved factors and captures the influence of factors that are not explicitly included as attributes. In this study, the ASC improves the model fit to real choices.

In the system under investigation, ports are considered as the senders. The ports are the starting points of shipments, where goods are loaded onto vessels or other modes of transportation for further distribution. Warehouses serve as receivers and are the locations where goods are stored. In this ABM, port agents and warehouse agents are created. The specific locations and attributes (e.g., cargoes) of the port and warehouses are determined accordingly. The port and warehouse agents were connected by road, rail and inland waterway networks. The mode-specific routes between a port and a warehouse are established. For each pair of origin and destination (OD), mode-specific routes were calculated using shortest route algorithms. e.g., when considering the freight train, the length of the rail network connecting the port and the nearest location to the warehouse was calculated based on OSM data.

Disaggregate models capture individual decision-makers' choices, while aggregate models consider groups or aggregates of decision-makers within a specific geographic zone. Disaggregate models are less commonly used in freight transport due to the limited availability of publicly accessible data, which is often considered sensitive and confidential by firms. In our study, we analyze modal share at an aggregate level by allocating freight flows across available modes for each OD pair, which is represented by a port and a warehouse. By explicitly modeling the location and spatial relationships between the port and warehouse agents, the model can provide a more realistic spatial representation. By modeling the freight flow and routes between OD pairs, this framework is able to calculate the mode-specific route distance traveled for transporting freight (given that load factors are known).

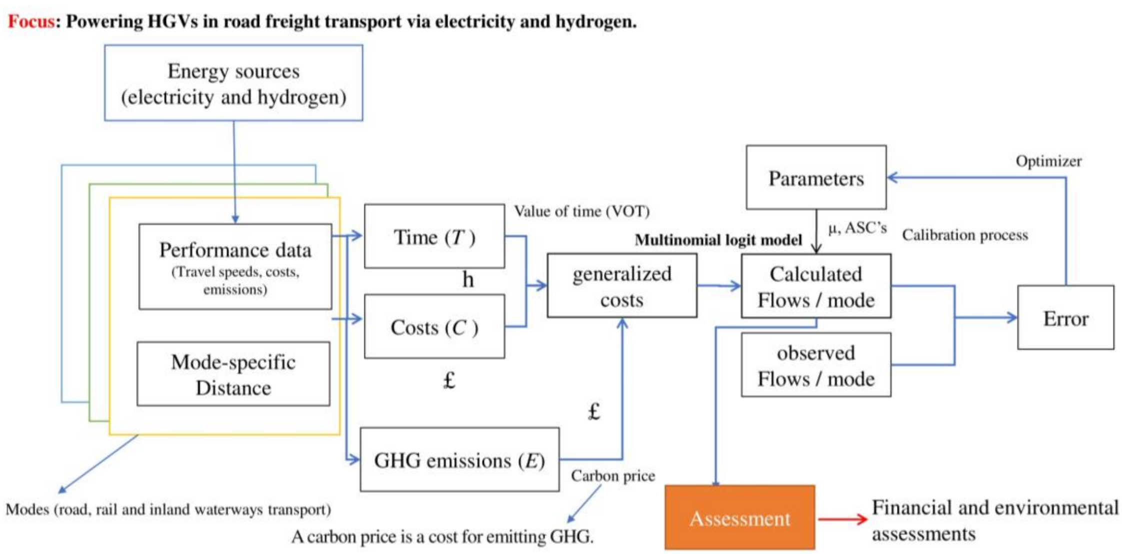

Figure 1: The overall modeling framework.

The use of different energy sources and vehicle technologies can have a significant impact on transport costs and emission costs. For example, battery HGVs powered by renewable energy sources may have lower carbon emissions and lower operational costs compared to vehicles powered by fossil fuels. To estimate the carbon impacts, we rely on emission data that captures the emissions associated with the transportation modes and technologies under consideration. Similarly, operating cost data is utilized to assess the financial implications of implementing these vehicle technology interventions in road freight. By incorporating data on energy consumption, carbon emissions, and route distance traveled between OD pairs, the developed modeling framework is able to analyze the cost and emissions impacts of adopting battery and hydrogen-powered HGVs.

In the modeling framework, As shown in Figure 1, the calibration uses an optimizer to find model parameter values so that its behavior in particular conditions matches a real or known pattern. Calibration is an important step in model development as it can help ensure that the model represents the system and can provide accurate assessment and useful insights. The model cannot be validated because we simulate future scenarios without real-world data, which is a common challenge in modeling future scenarios. However, we establish baseline scenarios using diesel-powered vehicles and compare them to scenarios involving battery HGVs and hydrogen-powered HGVs in road freight. In this comparison, we aim to assess the magnitude of benefits associated with the adoption of battery HGVs and hydrogen-powered HGVs relative to the baseline scenarios.

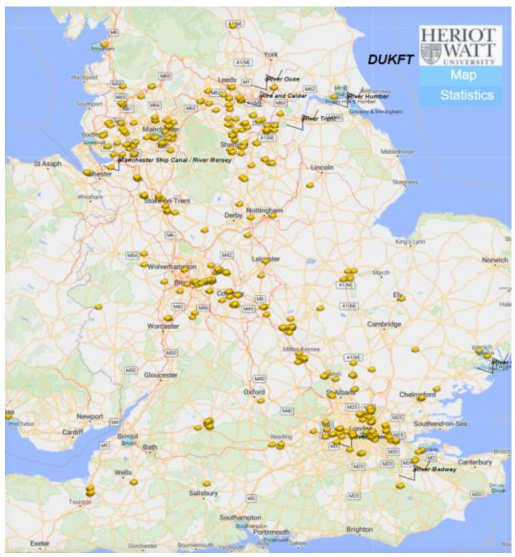

Figure 2: Snapshot of modeling simulation in Anylogic.

4 EXPERIMENTS SETUP AND INPUT DATA

This model is applied to the case of the Port of Immingham, its hinterland, and logistics operators who have freight flows from the Port of Immingham. The Port of Immingham is one of the largest dry ports in the United Kingdom. It is building a dedicated storage facility to keep pace with increased imports and provide transit storage for exports. The dry port is an inland intermodal terminal directly connected are directly connected by road, rail, and inland waterways to inland destinations (e.g., warehouse locations). The model is populated with real data.

- Demand attracted by warehouses is proportional to the total area of the warehouses. The main locations for 382 warehouses are in London metropolitan area (see Figure 2), the West Midlands (e.g., Birmingham), the Yorkshire and the Humber (e.g., Leeds), and North West England (e.g., Greater Manchester). The average warehouse size is about 30187 square meters, and the Total demand lifted by tonnage in the port of Immingham is 32.032 million tons.
- Transportation data: Travel times were then estimated based on the travel distances and average travel speeds. The average travel speed for road, rail, and IWW is set to 75 km/h, 32 km/h, and 8 km/h, respectively.
- In relation to the value of time (VoT), for road freight, the VoT is 5.28 per tonne hour. For rail freight, the VoT is 0.96 per tonne hour. This is significantly lower than the VoT for road freight.

For inland waterways transport, the VoT is the lowest among the three modes, at 0.046 per tonne hour.

- Vehicle characteristics: the vehicles for long-haul transportation are typical tractor-trailers (arctics). For example, a vehicle has a gross combined vehicle weight of 44 tonnes (with a payload of around 28 tonnes). They are the largest goods vehicles permitted on UK roads and are used to transport a large share of road freight. The annual mileage is 120,000 km. It is assumed that a shipment size equals the payload of a standard 44-tonne artic.

Table 1 provides estimates of the current and future WTW CO_2e emissions from alternative energy sources and vehicle technologies. The WTW emission CO_2e covers GHG emissions from the production and use of energy sources. The GHG emissions from hydrogen-power or battery HGVs (i.e., electric HGVs) are highly dependent on how the electricity or hydrogen is produced. Battery HGVs have the lowest levels of WTW GHG emissions both now and in the future.

Future production of hydrogen from electrolysis could significantly reduce greenhouse gas emissions. The emission for hydrogen-powered vehicles becomes lower; a diesel-powered freight train has a lower emission than diesel-powered HGVs and diesel-powered barges, and hydrogen-powered HGVs. There are significant uncertainties in energy production and vehicle production technologies. Data on current and future costs are limited and, to some extent, based on assumptions (Department for Transport 2018). As we move into the future, new energy and vehicle production technologies are expected to reduce operating costs. The determination of freight rates involves uncertainties and relies on assumptions that take into account mode-specific differences.

The modeling framework was developed using the AnyLogic proprietary platform (see Figure 2), and subsequently, the model was recreated using the Java programming language. By developing the model in Java, it became possible to customize it according to specific requirements.

Table 1: Estimates of the current (2020) and future (2030) WTW CO_2e emissions and operating costs.

Modes	Road			Rail	IWW
Vehicle types	Diesel-powered HGVs	battery HGVs	hydrogen-powered	Train (diesel)	Vessel (diesel)
WTW CO_2e emissions in 2020 (gCO_2e/ tonne-km)	41.14	21.89	36.96	26.5	36.81
WTW CO_2e emissions in 2030	41.142	2.18	7.69	26.5	36.81
Operating cost in 2020 (£/tonne-km)	0.037	0.025	0.031	Not use	Not use
Operating cost in 2030 (£/tonne-km)	0.037	0.019	0.023	Not use	Not use
Freight rate (£/tonne-km)	0.150	0.138	0.144	0.05	0.02

5 SIMULATION RESULTS AND DISCUSSION

5.1 Impacts of Zero-Emission HGVs Interventions

The first experiment using the ABM aims to test the impacts of adopting battery and hydrogen-powered HGVs. The impacts of the vehicle types are determined using the efficiency of the existing technologies and the expected efficiency of the technologies in 2030. In the current scenario (in 2020), battery HGVs offer a significant advantage in terms of carbon savings compared to hydrogen-powered HGVs. As shown in Table 2, the carbon savings achieved by battery HGVs is higher than hydrogen powered HGVs by a factor of 4. In the future scenario (in 2030), both battery HGVs and hydrogen-powered HGVs can contribute to significant carbon reductions. Specifically, battery HGVs achieve carbon reductions that are slightly higher than the reductions achieved by hydrogen-powered HGVs. It is suggested battery HGVs outperform hydrogen-powered HGVs both in terms of carbon savings and monetary benefits because of the low well-to-wheel emissions and costs of battery HGVs. Moreover, road freight transport that is electrified becomes attractive, and demand shifts slightly from rail and inland waterways freight transport to road freight transport.

Table 2: The impact of adopting battery and hydrogen-powered HGVs.

Mode	Current Demand share	Future Demand share	Mode	Current Demand share	Future Demand share
Rail (diesel)	6.135	6.072	Rail (diesel)	6.38	6.284
Road (battery)	89.581	89.689	Road (hydrogen)	89.163	89.327
Inland waterways (diesel)	4.284	4.239	Inland waterways (diesel)	4.457	4.389
Carbon emissions (million tCO2e)	25.116	6.345	Carbon emissions	39.427	11.709
Baseline emissions (million tCO2e) a	43.365	43.365	Baseline emissions	43.365	43.365
Carbon savings (million tCO2e) b	18.248	37.020	Carbon savings	3.938	31.655
Monetary benefits (million pounds) c	107400	107800	Monetary benefits	106800	107200

a) Diesel baseline emissions (million tCO2e); b) Carbon savings in road freight in the scenarios of replacing diesel-powered HGVs (million tCO2e); c) Monetary benefits in road freight = revenue- operating costs

Table 3: Estimates of WTW carbon emissions for alternative energy sources in the future (2030).

Demand \Carbon prices	£0/tCO2	£100/tCO2	£500/tCO2	£1000/tCO2	£2000/tCO2	£5000/tCO2
Rail (diesel)	6.142	6.072	5.799	5.468	4.849	3.341
Road (battery)	89.503	89.689	90.399	91.217	92.642	95.6
Inland waterways (diesel)	4.355	4.239	3.802	3.315	2.509	1.06
Carbon savings (million tCO2e) in replacement of diesel-powered HGVs	36.934	37.020	37.347	37.719	38.354	39.602
Rail (diesel)	6.337	6.284	6.072	5.813	5.316	4.016
Road (hydrogen)	89.168	89.327	89.942	90.657	91.923	94.686
Inland waterways (diesel)	4.495	4.389	3.986	3.53	2.762	1.298
Carbon savings (million tCO2e) in replacement of diesel-powered HGVs	31.590	31.655	31.905	32.192	32.689	33.708

The second experiment aims to test the impacts of different carbon prices, assuming expected vehicle energy efficiencies in 2030. Table 3 shows that as carbon prices rise, demand shifts from rail and inland waterways transport, which run on diesel, to the battery and hydrogen-powered HGVs-equipped road freight transport. As a result, there is a slight carbon emissions reduction benefit. However, this is far too small to be considered an effective means of reducing future carbon emissions. Moreover, compared with rail transport, inland waterways are more sensitive to increases in carbon prices, which discourage freight demand from being served via inland waterways transport. One of the main reasons for this could be diesel-powered freight vessels (barges) emissions are relatively higher than rail transport.

Simulation results suggest that technological interventions such as battery and hydrogen-powered HGVs will have a greater effect than carbon pricing in reducing carbon emissions. That is, carbon price increases cannot be the primary way to achieve a low-carbon future but should be considered to incentivize the use of low-carbon modes. Efforts to reduce carbon emissions should focus on fundamental system changes in energy sources used, vehicle technologies adopted, and their associated energy efficiencies.

5.2 Detailed Demonstrations of Modal Shares at the Level of Warehouses

As shown in Figure 3, demand shares for different transportation modes vary between the three warehouses. At Warehouse 1, road has the demand share (79.65 %), followed by rail transportation (11.26 %). We found that Warehouse 1 has a high IWW share of 9.09 %, indicating high use of inland waterways transport. In contrast, Warehouse 5 and 79 have no IWW share and rely on rail and road freight transport. This is because the warehouse is located in an area without convenient access to waterways transport. At Warehouse 79, road transportation has the highest demand share (97.84 %), with rail transportation accounting for only 2.16 % of demand. The warehouse is likely located in an area with poor access to rail infrastructure. The simulation results show that demand shares for different transportation modes can vary significantly between different warehouses, depending on factors such as location, infrastructure, and the types of goods being handled.

The mode share for different warehouses at different locations is likely to be influenced by different factors, including the location of the warehouse, services provided, and the quality of transportation infrastructure. The demand shares at each warehouse suggest that the availability and quality of transportation infrastructure, such as road and rail networks and access to waterways, has a significant impact on the transportation choices made by shippers. In such cases, infrastructure could play a more significant role than policy incentives in determining the demand shares for different transportation modes.

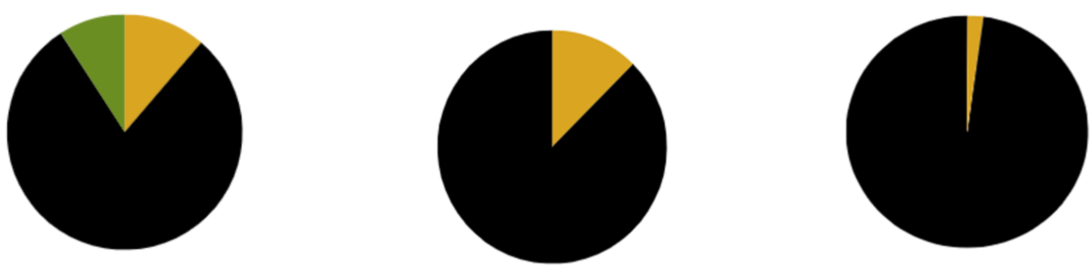

Figure 3: Mode shares for different warehouses at different locations.

6 CONCLUSIONS, LIMITATIONS, AND FUTURE DIRECTIONS

6.1 Conclusions

An ABM that can describe an inland multimodal freight system was developed. In this model, the freight was moved from ports to inland destinations (grouped warehouses) by road, rail, and inland waterways. The mode choice decision is made based on the travel cost and time, and carbon cost criteria. This work shows that the introduction of electric road freight vehicles will reduce the modal share of other carbon fueled modes and achieve significant carbon reductions. Furthermore, the work shows that carbon pricing has minimal effect on modal choice and carbon emission reductions while promoting technological innovations associated with vehicle energy efficiencies has a bigger impact on decarbonizations effort. Finally, the work has shown that battery HGVs generate a bigger overall benefit and larger carbon reduction than the adoption of hydrogen-powered HGVs.

When planning transportation policies and incentives, it is important to consider the infrastructure context of each warehouse location and prioritize investments in transportation infrastructure where necessary. By improving access to alternative transportation modes through infrastructure investments, policymakers can help to facilitate a more sustainable and efficient freight transportation system.

6.2 Limitations and future directions

Developing effective strategies for decarbonizing the inland multimodal freight transport system is full of challenges. The limitations of the existing ABM are identified, and future directions are recommended.

It is assumed that the port and warehouses can be fully connected by rail or inland waterway. In reality, for instance, a rail journey always includes a road journey (intermodal). Therefore, in the future, combined road-rail transport and combined road-inland waterway transport will be added to the choice set. Second, the inland multimodal freight system is modeled at an aggregate level where demand is split without considering product specificities. In the future, the modeling framework can be extended to model mode choices for individual shipments at a high spatial and temporal resolution. The ABM framework will be extended to analyze the share of different vehicle types within a mode, e.g., the share of battery and hydrogen-powered HGVs can be determined in road freight. Optimization algorithms will be used to determine the share of vehicle types. These techniques will enable us to identify the combination of vehicle types that minimizes environmental impact while meeting transportation demand. This will help transport planners, fleet operators, and city and port authorities to make the optimal infrastructure investment and the optimal decisions for fleet sizes and fleet profiles (e.g., types) in an inland multimodal freight system. Last but more importantly, further research is needed to conduct surveys or experiments to gather data on decision-makers' preferences towards different transport modes and vehicle technologies.

To meet the UK emissions target by 2030, increasing the fidelity scale of models such as the one developed in this work will be necessary. This will permit the evaluation of more carbon-reducing interventions, including land use and operational adaptation, to accelerate decarbonization efforts and inform science-based pathways to net zero. The need to rapidly evaluate multiple carbon-reducing interventions and combinations of interventions emphasizes the need to develop capacity and capability in developing and exercising these models.

Without these ABMs, removing uncertainty and de-risking will rely on the slow real world, small-scale, overly constrained, and costly trials and demonstrations. This will likely stall investment and put the carbon reduction commitments beyond reach.

ACKNOWLEDGMENT

We would like to extend our gratitude for the financial support provided by the Engineering and Physical Sciences Research Council under the grant 'Decarbonising the UK's Freight Transport' (grant number EP/S032061/1).

REFERENCES

Arencibia, A.I., M. Feo-Valero, L. García-Menéndez, and C. Román. 2015. "Modelling Mode Choice for Freight Transport Using Advanced Choice Experiments". *Transportation Research Part A: Policy and Practice* 75(C):252–267.

Axhausen, K. W. 2016. *The Multi-Agent Transport Simulation MATSim*. London: Ubiquity Press.

Bonabeau, E. 2002. "Agent-based Modeling: Methods and Techniques for Simulating Human Systems". *Proceedings of the National Academy of Sciences* 99(10):7280–7287.

Cantillo, V., J. Amaya, I. Serrano, V. Cantillo-García, and J. Galván. 2022. "Influencing Factors of Trucking Companies Willingness to Shift to Alternative Fuel Vehicles". *Transportation Research Part E: Logistics and Transportation Review 163*. 102753. https://doi.org/10.1016/j.tre.2022.102753.

De Bok, M., and L. Tavasszy. 2018. "An Empirical Agent-based Simulation System for Urban Goods Transport (MASS-GT)". *Procedia Computer Science 130:126-133*.

De Bok, M., L. Tavasszy, and S. Thoen. 2022. "Application of an Empirical Multi-agent Model for Urban Goods Transport to Analyze Impacts of Zero Emission Zones in The Netherlands". *Transport Policy* 124:119–127.

Department for Transport. 2018. "Transport Energy Model Report". Department for Transport. London.

Department for Transport. 2021. "Decarbonising Transport: A Better, Greener Britain". Department for Transport. London.

Gómez Vilchez, J. J., A. Julea, C. Lodi, and A. Marotta. 2022. "An Analysis of Trends and Policies Supporting Alternative Fuels for Road Freight Transport in Europe". *Frontiers in Energy Research* 10:1-14.

Haugen, M. J., D. Flynn, P. Greening, J. Tichler, P. Blythe, and A. M. Boies. 2022. "Electrification Versus Hydrogen for UK Road Freight: Conclusions from a Systems Analysis of Transport Energy Transitions". *Energy for Sustainable Development 68*: 203–210. https://doi.org/10.1016/J.ESD.2022.03.011

Hörl, S., F. Becker, and K. W. Axhausen. 2021. "Simulation of Price, Customer Behaviour and System Impact for a Cost-Covering Automated Taxi System in Zurich". *Transportation Research Part C: Emerging Technologies* 123, 102974.

Kaack, L. H., P.Vaishnav, M. G. Morgan, I. L. Azevedo, and S. Rai. 2018. "Decarbonizing Intraregional Freight Systems with a Focus on Modal Shift". *Environmental Research Letters*, 13(8). 083001.

Le, D. T., G. Cernicchiaro, C. Zegras, and J. Ferreira. 2016. "Constructing a Synthetic Population of Establishments for the Simmobility Microsimulation Platform". *Transportation Research Procedia*, 19:81–93.

Liu, J., K. M. Kockelman, P. M. Boesch, and F. Ciari. 2017. "Tracking a System of Shared Autonomous Vehicles Across the Austin, Texas Network Using Agent-based Simulation". *Transportation* 44(6):1261–1278.

Macal, C., and North, M. 2010. "Tutorial on Agent-based Modelling and Simulation". *Journal of Simulation* 4:151-162, DOI: 10.1057/jos.2010.3

Macal, C., and North, M. 2014. "Introductory Tutorial: Agent-Based Modeling and Simulation". Proceedings of the 2014 Winter Simulation Conference, edited by A. Tolk, S.Y. Diallo, I.O. Ryzhov, L. Yilmaz, S. Buckley, and J.A. Miller, 6–20. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Mckinnon, A. 2016. "Freight Transport in a Low-carbon World: Assessing Opportunities for Cutting Emissions". *TR News*, 2016-November (306).

Mulholland, E., J. Teter, P. Cazzola, Z. McDonald, and B. P, Ó Gallachóir. 2018. "The Long Haul Towards Decarbonising Road Freight – A Global Assessment to 2050". *Applied Energy* 216: 678–693.

Nassar, R. F., V. Ghisolfi, J. A. Annema, A. van Binsbergen, and L. A. Tavasszy. 2023. "A System Dynamics Model for Analyzing Modal Shift Policies Towards Decarbonization in Freight Transportation." *Research in Transportation Business and Management* 48. 100966.

Nicolet, A., R. R. Negenborn., and B. Atasoy. 2022. "A Logit Mixture Model Estimating the Heterogeneous Mode Choice Preferences of Shippers Based on Aggregate Data". *IEEE Open Journal of Intelligent Transportation Systems* 3:650-661.

Paddeu, D., and J. Denby. 2020. "Decarbonising Road Freight: Is Truck Automation and Platooning an Opportunity?". *Clean Technologies and Environmental Policy* 24:1021–1035.

Pearce, D., and E. O. Zdemiroglu. 2002. "Economic Valuation with Stated Preference Techniques Summary Guide". Department for Transport, Local Government and the Regions: London. www.dtlr.gov.uk

Regmi, M. B., and S. Hanaoka. 2015. "Assessment of Modal Shift and Emissions along a Freight Transport Corridor Between Laos and Thailand." *International Journal of Sustainable Transportation 9*(3):192–202.

Sakai, T., A. Romano Alho, B. K. Bhavathrathan, G. D. Chiara, R. Gopalakrishnan, P. Jing, T. Hyodo, L. Cheah, and M. Ben-Akiva. 2020. "SimMobility Freight: An Agent-Based Urban Freight Simulator for Evaluating Logistics Solutions". Transportation Research Part E: Logistics and Transportation Review 141.102017.

Samimi, A., K.Kawamura, and A. Mohammadian. 2011. "A Behavioral Analysis of Freight Mode Choice Decisions". *Transportation Planning and Technology* 34(8):857-869.

Tao, X., Q. Wu, and L. Zhu. 2017. "Mitigation Potential of CO2 Emissions from Modal Shift Induced by Subsidy in Hinterland container transport". *Energy Policy* 101:265-273.

Van Grinsven, A., M. Otten, E. Van Den Toorn, R., Van Der Veen, J. Király, and R. Van Den Berg. 2021. "Research for TRAN Committee-Alternative Fuel Infrastructures for Heavy-Duty Vehicles". European Parliament, Policy Department for Structural and Cohesion Policies, Brussels.

Wang, S., G. H. de A., Correia. and H. X. Lin. 2022. "Modeling the Competition between Multiple Automated Mobility on-Demand Operators: An Agent-Based Approach". *Physica A: Statistical Mechanics and Its Applications* 128033.

Yan, S., K. de Bruin, E. Dennehy, and J. Curtis. 2021. "Climate Policies for Freight Transport: Energy and Emission Projections through 2050". *Transport Policy* 107:11–23.