A SYSTEM DYNAMICS-BASED ANALYSIS ON THE TIME RESPONSE OF FREIGHT TRANSPORT SYSTEM TO DECARBONIZATION MEASURES

Verônica Ghisolfi

Tese de Doutorado apresentada ao Programa de Pós-graduação em Engenharia de Transportes, COPPE, da Universidade Federal do Rio de Janeiro, como parte dos requisitos necessários à obtenção do título de Doutora em Engenharia de Transportes.

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TESE SUBMETIDA AO CORPO DOCENTE DO INSTITUTO ALBERTO LUIZ COIMBRA DE PÓS-GRADUAÇÃO E PESQUISA DE ENGENHARIA (COPPE) DA UNIVERSIDADE FEDERAL DO RIO DE JANEIRO COMO PARTE DOS REQUISITOS NECESSÁRIOS PARA A OBTENÇÃO DO GRAU DE DOUTORA EM CIÊNCIAS EM ENGENHARIA DE TRANSPORTES.

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Verônica Ghisolfi

Fevereiro/2023

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O transporte de cargas é uma fonte de emissões de gases de efeito estufa em um cenário global voltado para a redução de emissões. A descarbonização do setor é desafiadora pela dependência de combustíveis fósseis, enquanto esforços para redução de emissões não são implantados com a agilidade adequada para atender às metas climáticas. Essa tese visa analisar as dinâmicas do sistema de transporte de cargas em relação a implementação de políticas de descarbonização. A Dinâmica de Sistemas destaca-se pela sua adequação para investigar o impacto de políticas e estratégias ao longo do tempo, considerando-se a complexidade dinâmica dos sistemas estruturados em laços de causa-e-efeito e atrasos entre os diversos elementos do sistema. A revisão bibliográfica evidenciou uma lacuna quanto a exploração adequada das dinâmicas que regem o tempo de resposta do sistema. Baseando-se na lacuna existente, propôs-se um modelo conceitual representado por diagramas de causa-e-efeito, explorando as interações entre seus componentes e os pontos de alavancagem do sistema. Por fim, um modelo de simulação foi desenvolvido e aplicado ao sistema de transporte de cargas brasileiro. Os resultados evidenciaram a necessidade de um conjunto de políticas para a descarbonização do setor. Quanto mais cedo as políticas forem aplicadas, melhor será o abatimento das emissões no longo prazo. Os atrasos na implementação das políticas devem ser analisados com cautela, para que políticas de curto prazo não prejudiquem os benefícios das políticas de longo prazo.

Abstract of Thesis presented to COPPE/UFRJ as a partial fulfillment of the requirements for the degree of Doctor of Science (Dr.Sc.)

A SYSTEM DYNAMIC-BASED ANALYSIS ON THE TIME RESPONSE OF FREIGHT TRANSPORT SYSTEM TO DECARBONIZATION MEASURES

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Freight transport represents a source of greenhouse gas emissions in a global scenario aimed at reducing emissions. The decarbonization of this sector is challenging due to the high dependence on fossil fuels, while efforts to reduce emissions are not implemented fast enough to meet climate goals. This Ph.D. dissertation aims to analyze the dynamics that govern the time response of the freight transport system to decarbonization measures implementation. Given the complexity of the freight transport system, System Dynamics stands out for its suitability to investigate the impact of policies and strategies over time, considering the dynamic complexity of systems structured in feedback loops and delays between the system's elements. A literature review showed a gap regarding the adequate exploration of the dynamics that govern the system's time response to the implementation of decarbonization measures. Based on this gap, a conceptual model was proposed through a causal loop diagram, exploring the interactions between its components and the dynamic levers of the system. Finally, a simulation model was developed and applied to the Brazilian freight system. The results evidenced that a set of measures is needed to achieve a compelling decarbonization result. The sooner the measures are enforced, the better the emissions abatement in the long run. The delays in their implementation should be carefully analyzed, since nearsighted policymaking may hinder their benefits in the long term.

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1 Introduction

This chapter addresses some aspects related to the need to decarbonize the freight transport system to mitigate global warming and climate change. We highlight the necessity for decision-support instruments, capable of evaluating the emission reduction potential of decarbonization measures and the dynamics involved in the implementation process to timely reach the established goals. The objective and research questions for this study are also presented, as well as the structure of the dissertation.

1.1 Background and motivation

Freight transport is a key element of supply chains and a reflection of a dynamic economy. Being almost exclusively powered by fossil fuels, it brings environmental negative externalities. Global freight transport was the source of 2.9 billion tons of carbon dioxide (CO_2) emissions in 2015 (or more than 7% of global emissions), which is expected to more than double by 2050 if business continues as usual (INTERNATIONAL TRANSPORT FORUM – ITF, 2019). Advanced technologies and green practices to improve freight transport energy efficiency exist, but they are not being deployed nearly fast enough to deliver the savings needed to meet climate targets in the face of increasing demand (ITF, 2019; INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE – IPCC, 2019). Without a widespread and concerted effort, freight transport is set to overtake energy as the most carbon-intensive sector by 2040 (GREENE and FAÇANHA, 2019).

While fossil fuel use by passenger vehicles is trending downward, fuel consumption and emissions from freight are on the rise (FRIDELL et al., 2019). An analysis of long-term carbon reduction plans for transport in 60 countries revealed that they referred three times more to passenger-related improvement measures than freight measures, even though freight transport accounts for 40% of transport's CO_2 emissions (GOTA et al., 2016) and road freight transport accounts for about 7% of the world's energy-related CO_2 emissions (KAACK et al., 2018). Achieving a more sustainable freight transport system is a world goal to reduce emissions, improve human health and reduce negative environmental impacts (OLSSON et al., 2015).

Emissions reduction from freight transport can be achieved by combining different decarbonization measures or policies, such as the modal shift to more sustainable modes, increasing vehicle energy efficiency, using low or zero-carbon fuels, and improving the operational efficiency of the freight logistics (KAACK et al., 2018; MCKINNON, 2018). This is only possible with top-down interventions since the freight transport sector represents a complex social, technical, and economic system, which depends on government actions, different policymakers, and stakeholders to be adapted, changed, or innovated (GOLDMAN and GORHAM, 2006). Enforcement laws, for example, are a way to trigger a transition and to improve the sector in different areas such as technology, efficiency, and emissions (GUDMUNDSSON et al., 2016). In this thesis, the decarbonization measures are also referred to as policy measures, independently of the specific stakeholders responsible for the implementation of the actions.

Given the carbon reductions required for the next few decades, decarbonization must be approached systematically, fully exploiting all the opportunities. No single technology, software tool, or business practice has the potential to cut emissions by the required amount (MCKINNON, 2018). There are, fortunately, a multitude of strategies that businesses can do to reduce the carbon footprint of their logistics operations, offering flexibility and diversity, but also making the development of a decarbonization strategy more complex. For example, stakeholders must understand the variables of the logistics set to provide infrastructure, tools, policies, and decisions capable of enabling national production and movement, by managing them in a socially and environmentally appropriate manner. This logistics set can be seen as a complex system involving feedback responses with different time lags between each agent's decisions (SHEPHERD, 2014). According to ABBAS and BELL (1994), three main areas change dynamically in transport systems: the travel demand; the technology and level of supply of transport services and facilities; and the evaluation criteria on which decision-making is based. The evolution over time of the freight transport system is taken into account by stakeholders who take decisions according to the system's changes. The system intervention may create unanticipated side effects, leading to resistance, and the tendency for interventions to be delayed, diluted, or defeated by the response of the system intervention itself (MEADOWS, 1982), impacting the evolution of the system in many directions.

Thus, besides the mechanisms to decarbonize freight transportation, we must also understand the internal dynamics involved in this process, how long they take their effects in different scenarios to improve the forecasting and planning of freight transport decarbonization strategies within the time frames imposed by the urgency to reduce global emissions.

Since freight transport represents a multi-dimensional system, discrete modeling approaches do not cater to the dynamic interactions that exist between its elements, so a system-based approach, with an efficient procedure for representing, analyzing, and planning complex systems, is needed. For this purpose, System Dynamics (SD) method stands out due to its adequacy for investigating the impact of policies and strategies over continuous time taking into account the dynamic complexity of feedback loops structured systems (MAALLA and KUNSCH, 2008; YLÉN and HÖLTTÄ, 2007). ABBAS and BELL (1994) presented the advantages as well as the limitations of using SD as a modeling framework for transportation systems and stated that SD should be applied in strategic studies that are concerned with policy analysis and decision-making in the field of transportation.

1.2 Research objective and research questions

The previous subsection presented the problem and the variety of policy measures for freight transport decarbonization. It indicates that for the successful solution of freight transport emissions-related problems, we need to understand the dynamics of the freight transport system. This is possible by mapping the system structure and feedback loops, the interactions between stakeholders' decisions that potentially change the current status of the system. The System Dynamics approach is suited for understanding the complexities of the freight transport system. Using this technique, we can model and map the details of continuously and dynamically changing characteristics of the freight transport system decarbonization. In this dissertation, the objective is folded out in the form of research questions where each question represents a specific research direction. By exploring these research directions, this Ph.D. dissertation will evaluate their importance and incorporate them into the model development framework.

Accordingly, the focus of this research is to analyze the dynamics of the freight transport system toward decarbonization. So, we aim to integrate the important aspects of modeling and provide a practical guide for the development of a well-articulated and feasible system dynamics model for the freight transport decarbonization domain.

With the scope of the research defined, we formulate the objective of the dissertation as:

> "To analyze the dynamics that govern the time response of the freight transport system towards decarbonization."

Freight transport decarbonization has generated interest among the government, researchers, companies, and environmentalists. Studies and analysis are aimed at gaining a better knowledge of the dynamics of the freight transport domain to solve emissions-related problems. The review of the methodical approaches for model and solving these problems can critically summarize the current knowledge, identify strengths and trends of the research in the field and detect the unattended gaps.

The freight transport decarbonization system depends on and involves decisions related to the demand for goods, the transport infrastructure to be used, the efficient use of vehicle fleets, the energy efficiency, and the fuels used. Although these decision spheres impact each other, current models deal with them isolated and researchers have not yet fully succeeded in understanding the dynamics between them within the freight transport decarbonization system. Using the reviewed modeling efforts from this domain, we can explore the limitations, and identify missing links and dynamics knowledge in the current models. Hence, the first research question is:

I. **What are the gaps in the dynamics of freight transport decarbonization research?**

Many researchers, modelers, and real-world stakeholders explain their mental models of the same process or entity in different ways. For a better understanding and a more efficient information exchange, a common mental model helps to communicate the information without ambiguity. For this reason, an efficient mechanism is needed to explore the dynamics of the freight transport system. In the wake of this need, the next research question is:

II. **How can we conceptually model the dynamics of the freight transport system to decarbonization measures?**

In this sense, Systems Dynamics can capture rebound effects, contributing to the understanding of how the elements interact in a system. These models are based on Causal

Loop Diagrams (CLD) which represent, in a qualitative way, how the variables change and affect each other over time. The quantitative components of the Stock and Flow Diagrams can be added in the form of rules of the evolution of the system which can be stocks and flows, delays, and dynamic levers aiming at explaining and predicting the evolution of a dynamic system in the long run. The insights gained from such a model can be used to create a knowledge base of the system and its emerging patterns for generating appropriate solutions to the problems associated with freight transport decarbonization.

The freight transport decarbonization system includes a variety of economic, social, legal, and technological aspects. In this situation, it is essential to draw the boundary on the amount of detail to be included in the model. This choice is dependent on the required precision of the model which, in turn, is directly related to the type of information and knowledge that is required. Thus, there are many different ways in which an SD model can be developed for the freight transport decarbonization system. Therefore, the next important research question is:

III. How can we quantitatively model the multiple dynamics of the freight transport decarbonization system?

The freight transport system is a complex sector to decarbonize with a large number of heterogeneous stakeholders. Successful decarbonization measures implementation should take into account the internal dynamics of the system. However, it is a challenging task to determine the precision required to model such a system, and based on the complexity desired, some assumptions are unavoidable in this context.

1.3 Dissertation structure

The dissertation structure is presented in Figure 1.1.

Chapter 1: Introduction	**Chapter 2: Literature Review**	**Chapter 3: Conceptual Model**	**Chapter 4: Simulation Model**	**Chapter 5: Conclusions**
▪ Background and motivation ▪ Research objective ▪ Research questions ▪ Thesis structure	▪ Review of system dynamics models applied in freight transport decarbonization	▪ Causal loop diagram of decarbonization measures for freight transport system and their dynamic levers	▪ Stock and flow diagrams with mathematical equations ▪ Validation tests ▪ Case study application and results	▪ Conclusions ▪ Future research

Figure 1.1 – Dissertation structure.

Chapter 1 presents a general introduction to the freight transport domain by discussing the environmental problems associated with its emissions and possible decarbonization measures. Finally, the chapter introduced the research objective and associated research questions, besides the dissertation structure.

Chapter 2 is a paper published in the Sustainability journal (see GHISOLFI et al., 2022a). It reviews the literature regarding the system dynamics models addressing freight transport decarbonization systems. The chapter presents the motivation for the review and the review itself is presented which is followed by a discussion of the results. The chapter concludes by giving an overview of the trends and gaps in the dynamics of freight transport decarbonization modeling to answer the first research question of the dissertation.

Chapter 3 is a paper published in the Journal of Simulation (see GHISOLFI et al., 2022b). It proposes a conceptual model for the freight transport decarbonization system through causal loop diagrams. The chapter details the dynamics of the system bringing a broad view with five decarbonization measures, the feedback loops among their components, and the dynamic levers that govern the time response of the system to the policy instruments applied. This chapter answers the second research question of the dissertation.

Chapter 4 is in a paper format and it will be submitted to a scientific journal. It deals with the quantitative modeling of the freight decarbonization system through stock and flow diagrams which, along with its structures, time delays, and nonlinearities; determine its dynamics. As the feedback loops interact, the dynamics are not intuitive and computer simulation is used to deduce the model behavior. The model is applied to the case study of the Brazilian freight transport system. Then, it is tested and submitted for sensitivity analysis. Results are presented and discussed. The third research question of the dissertation is answered by this chapter and its supplementary material (model equations, policies equations, and model results) are presented in Appendices A, B, and C.

Chapter 5 presents the conclusions, limitations, and suggestions for future research.

Figure 1.2 shows the research framework relating the research questions with each chapter, their specific research objectives, and the general objective.

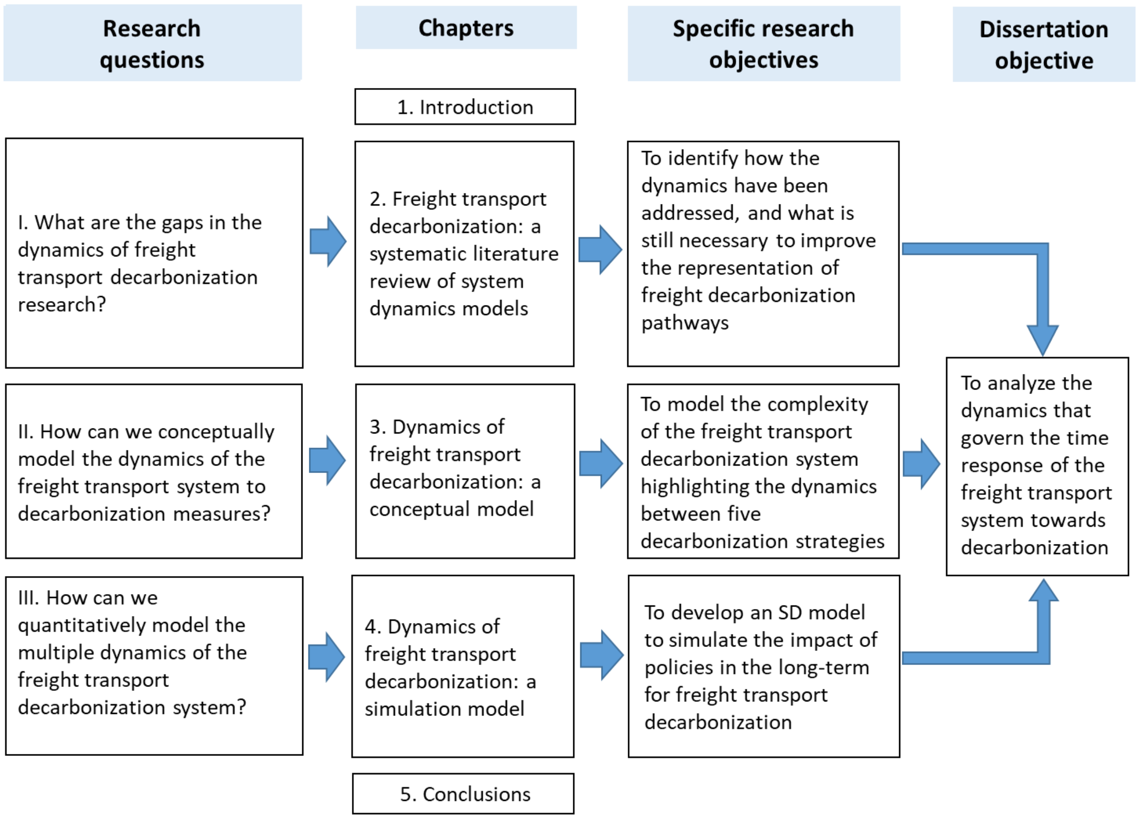

Figure 1.2 – Research framework.

2 Freight transport decarbonization: a systematic literature review of system dynamics models

This chapter presents a systematic literature review of system dynamics models related to freight transport decarbonization systems. Published in the Sustainability journal (GHISOLFI et al., 2022a), we chose to keep the structure, form, and text as close as possible to the published paper. Firstly, we present the motivation, then the review of the models is presented and the results are discussed. The chapter concludes by giving an overview of the trends and gaps in the dynamics of freight transport decarbonization modeling.

2.1 Introduction

The freight transport sector contributes to resource consumption, pollution, and climate change, mainly due to the increasing demand for, and burning of, fossil fuels (THE WORLD BANK, 2017). Road freight alone accounts for about 7% of the world's energy-related carbon dioxide (CO_2) emissions (KAACK et al., 2018), with a likelihood of increasing in the future despite progress in mobility electrification. This continued growth in emissions is mainly due to globally increasing consumption and, therefore, an increase in freight trips, which are still primarily based on internal combustion vehicles (INTERNATIONAL ENERGY AGENCY – IEA, 2019).

Decarbonization of the transport sector can only be achieved by combining several strategies with top-down policies (KAACK et al., 2018). The green logistics framework presents five strategies as the forward path to decarbonizing freight transportation (MCKINNON, 2018): (1) reducing freight transport demand; (2) shifting freight to lower-carbon transport modes; (3) improving assets utilization; (4) increasing energy efficiency; (5) switching to lower-carbon energy. Different policy instruments deal with the implementation of each decarbonization strategy. Modal shift, for example, can be achieved by employing fiscal measures (e.g., rail freight funding), regulatory measures (e.g., regulation of truck weight or size), and infrastructure investment (BICKFORD et al., 2014). Regardless of the decarbonization strategy adopted, decision-makers must be aware that their policies, decisions, and actions may have second-order effects on the system, leading to the need for a macro view that enables addressing the problem in a systemic and integrated way.

To illustrate the problem, in some countries, the discussion focuses on using larger and heavier trucks to transport more freight instead of shifting to rails or waterways (IEA, 2017). Increasing the payload of trucks can decrease environmental impacts, as evidenced by a case study in China (HAO et al., 2012), and operating costs of the road mode by ton-km, as evidenced by the case study of the transport of ornamental stones in Brazil (GHISOLFI et al., 2019). However, the efficiency increase leads to a rebound effect over freight transport demand (JONG et al., 2010), worsening the system's general state. This example demonstrates that a change in the vehicle system, without considering the freight demand mechanism, may not achieve the expected goal. Moreover, reducing road freight operating costs discourages the modal shift to cheaper modes, such as rail and waterways (IEA, 2017), which can hinder achieving global environmental goals imposed by climate change. On the other hand, if transport agents direct efforts toward a modal shift from road to rail, they must consider possible reactions from road haulers. Otherwise, the existing economic competition can undermine rail operations, whose competitive advantage depends on a constant freight flow. Freight transport decarbonization is a dynamic, complex system; in the decision-making process, one strategy may impact the other.

Besides the impacts of second-order effects, the system's dynamics are also determined by the speed of change of its subsystems, i.e., the time that each decision or action takes to be implemented and take effect. In this sense, developing cleaner technologies and alternative fuels are relevant strategies for freight decarbonization, but knowing how long these technologies will take to be adopted by transport companies and used on a large scale is critical for crafting more realistic decarbonization targets and addressing the problem more efficiently. For example, in Brazil, ethanol and biodiesel have a long trajectory as national fuels, which were initially used to reduce dependence on oil imports during the oil crisis in the 1970s. In later decades, the ethanol and biodiesel industries suffered several political and economic impacts that delayed their full development (JONG et al., 2021). Currently, the legislation requires the use of a minimum of 27%

ethanol in gasoline and 10% biodiesel in diesel (PETRÓLEO BRASILEIRO – PETROBRAS, 2022), failing to meet previously established targets.

Given the presented context, TAVASSZY (2020) highlights the importance of studies involving time-definite policy objectives and their impacts on the dynamics of freight systems. The system dynamics (SD) modeling approach is suitable for investigating the effects of policies and strategies over a continuous time in complex systems (MAALLA and KUNSCH, 2008; YLÉN and HÖLTTÄ, 2007). SD has been a powerful tool for policymakers to predict system changes and future scenarios in different contexts, the most well-known being the Limits to Growth study by the Club of Rome in 1972 (MEADOWS et al., 2004). ABBAS and BELL (1994) were the first to discuss and evaluate the strengths and weaknesses of SD concerning its suitability and appropriateness for transportation systems modeling, pointing out that it is well suited for modeling strategic issues and supporting policy analysis and decision-making processes. In SHEPHERD (2014), a review of SD studies was presented, categorizing them by area of application in transportation studies and summarizing insights and recommendations for future application of the SD approach in this field. Interestingly, SHEPHERD (2014) mentioned just one study related to freight transport and environmental impacts. The discussion about alternative fuel vehicles was kept around the passenger transport system, which shows the lack of sufficient research in freight transport and decarbonization with this approach.

Other literature reviews on specific strategies of transport emission mitigation generally cover only a very particular component of the system or the measures to reduce emissions. SD models regarding alternative powertrain technology, particularly electric vehicles, have been reviewed by VILCHEZ and JOCHEM (2019), evidencing that the models differ in purpose and assumptions, particularly about consumer choice of powertrains. GNANN and PLÖTZ (2015) reviewed different modeling approaches, which focused on the interaction of the market diffusion of alternative fuel vehicles and their refueling infrastructure; dynamics for truck fleet change were not considered. Some authors reviewed top-down and bottom-up models for carbon emissions measurement from road traffic (MCKINNON and PIECYK, 2009; DEMIR et al., 2011; DEMIR et al., 2014; ZHANG et al., 2019) and summarized the main factors influencing traffic carbon emissions, including vehicle speed, load, acceleration, and road slope. FONTOURA and RIBEIRO (2021) reviewed SD models in developing and implementing urban policies focused on sustainable transportation, specifically the economy, environment, land use, social, and traffic congestion policies for motorized and non-motorized modes. REBS et al. (2019) provide a review of sustainable supply-chain-management-related SD models, including forward, reverse, and closed-loop supply chains that include environmental or social aspects of sustainability. Interestingly, none of these literature reviews covered the dynamics involved in a broad range of decarbonization strategies for freight transportation. The time dependency of measures and their impacts are modeled in some cases but not explicitly discussed as a component of the policies under investigation.

Considering the importance of decarbonizing freight transport and SD's contribution to its dynamic analysis, the absence of a review dedicated to this problem motivated this study. The research question is: How have the dynamic aspects of freight transport decarbonization systems been modeled using the system dynamics approach? This systematic literature review aims to identify the feedback responses that have been modeled, how the dynamics have been addressed by SD models so far, and what research is still necessary to improve the representation of decarbonization pathways with SD models. To accomplish this objective, the remainder of this chapter is organized as follows. Section 2.2 details the methods adopted in this systematic literature review. Section 2.3 presents the main results according to different decarbonization strategies. Finally, Section 2.4 sets out the final remarks of the chapter and indicates future research directions.

2.2 Materials and Methods

This chapter presents a systematic literature review focused on studies that evaluate decarbonization strategies for freight transport using an SD approach. PRISMA guidelines were used for the literature review process (MOHER et al., 2009). The portfolio was built in July 2021 using the Google Scholar database covering the available online journals, unpublished studies, conference proceedings, industry trials, technical reports, and similar publications, with neither time nor geographical constraints. Thus, criteria such as journal rankings were not used for exclusion purposes because this review aims to give a comprehensive overview of the system dynamics models of freight transport decarbonization. Moreover, other databases were not used to avoid repeated papers in the portfolio, considering that Google Scholar makes all electronic resources available (FALAGAS et al., 2007).

The search procedure was performed using the following keywords: "decarboni*", "emission", "freight transport *", and "system dynamics". The truncated words were used to obtain their possible variations and different spellings. The search resulted in 980 studies. All repeated studies, books, and non-English materials were removed from the sample. Then, the inclusion criteria were checked by reading all the titles, abstracts, and keywords. Finally, the portfolio of studies to be reviewed and analyzed in more detail was obtained by applying the exclusion criteria. Figure 2.1 shows the flow diagram of the literature review process based on the PRISMA guidelines (MOHER et al., 2009).

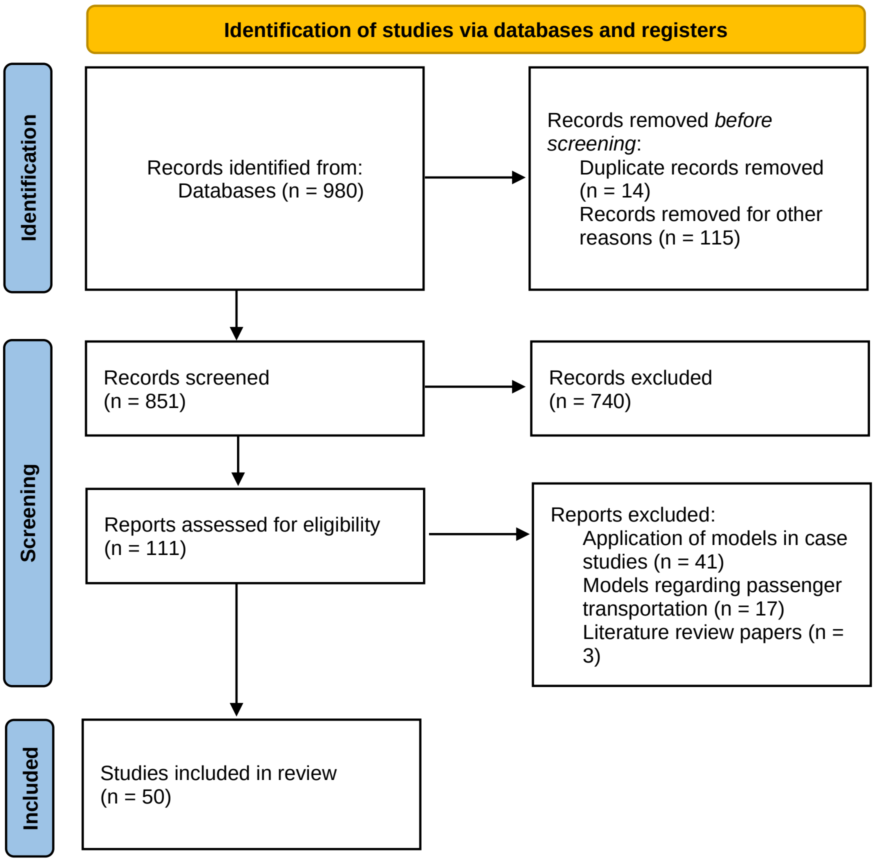

Figure 2.1– Flow diagram of the systematic literature review proceeding according to PRISMA. Source: MOHER et al. (2009).

In the first screening step, we applied the inclusion criteria to select papers containing system dynamics models regarding the freight transport sector and emission issues or decarbonization strategies, which resulted in 740 exclusions and 111 publications being assessed for eligibility. In the second screening step, despite citing freight transport, a few studies were identified concerning passenger transport and were disregarded for review by applying the exclusion criteria. Specific and well-established models, such as ASTRA and ESCOT, were used in many case studies; however, only the studies regarding the models' development were included instead of all their case study applications. The literature-review-selected papers were already described in Section 2.1. In summary, 50 studies of decarbonization strategies for freight transport using the SD approach remained in the portfolio to be reviewed in the following section.

The papers were identified and analyzed by each decarbonization strategy. Different frameworks support managers and policymakers in conceptualizing and formulating coherent decarbonization strategies to assess various drivers and opportunities for reducing emissions. The green logistics framework (MCKINNON, 2018) was used because it includes a wide range of aspects of freight transport with five strategies: (i) reducing freight transport demand – within the bounds of logistics management, this involves reducing the freight transport intensity of economic activity; (ii) shifting freight to lower-carbon transport modes – taking advantage of the wide variations in carbon intensity between modes; (iii) improving assets utilization – using vehicle and warehouse capacity more effectively; (iv) increasing energy efficiency – reducing energy consumption relative to freight ton-km and warehouse throughput; (v) switching to lower-carbon energy – reducing the carbon content of the energy used in logistics. This framework incorporates diversified approaches in multi-disciplinary green road freight transportation research (MEYER, 2020).

Besides the green logistics framework, the TIMBER (an acronym for technology, infrastructure, market, behavior, energy, and regulation) framework (MCKINNON, 2018) was also used to identify external forces needed to support the previous strategies. In addition to decarbonization strategies and the necessary external factors to support them, the policy instruments simulated in the SD models were also identified. Four policy categories were considered based on STELLING (2014): economic, legal, knowledge-based, and societal instruments. Economic instruments concern internalizing external costs by imposing taxes, charges, fees, tax exemptions, subsidies, etc. Legal instruments are laws, regulations, and norms, such as size and weight restrictions of vehicles, obligation schemes of fuel composition, maintenance, and performance-based standards. Knowledge-based instruments are information and research and development (R&D). Information can influence behavior and knowledge, hence increasing the acceptance of other instruments. R&D relates to creating and finding new solutions, such as improving energy efficiency and making transport independent of fossil fuels. Finally, societal instruments are infrastructure investments in alternative modes, carbon-neutral techniques, such as electrical roads, and infrastructure for loading/filling up electric or hydrogen-gas-driven vehicles. Figure 2.2 depicts the interactions between external factors, decarbonization strategies, and policy instruments identified in the SD models.

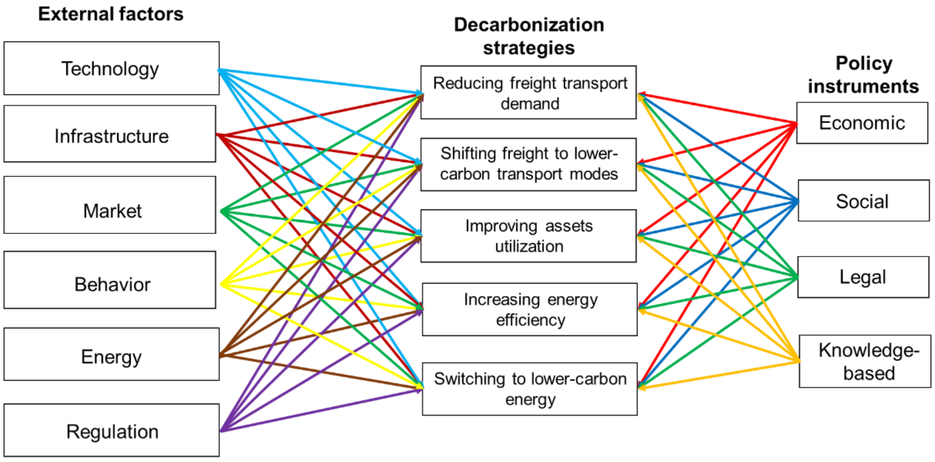

Figure 2.2 – Relations between external factors, decarbonization strategies, and policies.
Source: based on MCKINNON (2018).

The following section describes the SD models and dynamics of freight transport decarbonization. The dynamic aspects assessed in the SD models included assumptions made to build the feedback loops, causal loop diagrams, stock and flow diagrams, time-related variables, or delay equations. These factors influence the system's behavior over time and the results achieved in the long term.

2.3 Results

This section discussed and analyzed the selected papers to construct a view of the state-of-the-art factors in modeling freight transport decarbonization using SD. Table 2.1 presents the selected studies, their case study, geographic level, simulation period, SD software used, and whether or not the model diagrams (causal loop diagrams – CLD and stock and flow diagrams – S and F) were fully or partially presented.

Table 2.1 – Studies of SD models for decarbonization of freight transportation.

Study	Case Study	Geographic Level	Simulation Period[1]	Software	Model
AGHA et al. (2019)	Iran	Nation/Region	2009–2034	Vensim	✓
ASCHAUER (2013)	Qualitative	Nation/Region	-	Stella	✓
ASCHAUER et al. (2015)	Generic	Nation/Region	10 years	Stella	✓
AZLAN et al. (2019)	Malaysia	Nation/Region	1990–2016–2040	Powersim	✓
BARISA and ROSA (2018a)	Latvia	Nation/Region	2013–2030	Powersim	S and F *
BARISA and ROSA (2018b)	Latvia	Nation/Region	2016–2030	Powersim	CLD
CAGLIANO et al. (2015a)	Italy	Urban	120 months	Vensim	CLD
CAGLIANO et al. (2015b)	Italy	Urban	120 months	Vensim	CLD
CAGLIANO et al. (2017)	Italy	Urban	120 months	Vensim	✓

Study	Case Study	Geographic Level	Simulation Period[1]	Software	Model
CHOI et al. (2019)	South Korea	Nation/Region	100 months	Vensim	✓
BRITO JUNIOR et al. (2011)	Brazil	Nation/Region	2010–2025	Vensim	✓
DOLL et al. (2010)	Europe	Nation/Region	2005–2025	Not specified	-
DONG et al. (2019)	China	Urban	2017–2035	Vensim	✓
ERDMANN et al. (2004)	EU15	Nation/Region	2000–2020	Powersim	-
FIORELLO et al. (2010)	Europe	Nation/Region	1990–2050	Vensim	-
FREEMAN et al. (2015)	UK	Nation/Region	1970–2010–2030	Vensim	✓
GENG et al. (2017)	China	Nation/Region	2015–2025	Vensim	✓
HADDAD et al. (2019)	Lebanon	Nation/Region	2010–2040	Vensim	S and F *
HAMOUDI et al. (2021)	Generic	Nation/Region	10 years	Vensim	✓
HAN and HAYASHI (2008)	China	Nation/Region	2000–2020	Not specified	✓
HIDAYATNO et al. (2019)	Qualitative	Urban	-	Vensim	CLD
HILTY et al. (2006)	EU15	Nation/Region	2000–2020	Powersim	-
HU et al. (2019)	China	Urban	2007–2035	Vensim	✓
HUANG et al. (2021)	China	Nation/Region	2001–2019	Vensim	✓
KAR and DATTA (2020)	Qualitative	Nation/Region	-	Vensim	CLD
KRAIL and KÜHN (2012)	Germany	Nation/Region	2009–2050	Not specified	-
KUNZE et al. (2016)	Qualitative	Urban	-	Anylogic	S and F *
LEWIS et al. (2014)	Qualitative	Nation/Region	-	Stella	CLD
LEWIS et al. (2015)	Qualitative	Nation/Region	-	Not specified	-
LIU and MU (2015)	China	Nation/Region	2015–2024	Vensim	-
LIU et al. (2017)	China	Nation/Region	2016–2025	Vensim	-
LIU et al. (2019)	China	Nation/Region	2008–2030	Not specified	-
LIU et al. (2021)	China	Nation/Region	2020–2035	Vensim	-
MELKONYAN et al. (2020)	Austria	Urban	2018–2030	Vensim	✓
MENEZES et al. (2017)	Brazil	Urban	2010–2040	Vensim	-
OUMER et al. (2015)	Generic	Nation/Region	15 months	iThink	
PURWANTO et al. (2011)	Global	Nation/Region	2000–2050	Vensim	CLD *
ROZENTALE et al. (2020)	Latvia	Nation/Region	1990–2050	Stella	S and F *
SCHADE and SCHADE (2005)	Germany	Nation/Region	1990–2030	Not specified	-
SEITZ (2014)	Qualitative	Nation/Region	-	Vensim	CLD
SEITZ and TERZIDIS (2014)	Germany	Nation/Region	2010–2035	Vensim	CLD
SETIAWAN et al. (2019)	Indonesia	Nation/Region	2020–2050	Vensim	CLD *
SHAFIEI et al. (2014)	Iceland	Nation/Region	2012–2050	Not specified	-
SIM (2017)	South Korea	Nation/Region	2015–2030	Vensim	✓
THALLER et al. (2016)	Qualitative	Urban	-	Vensim	✓
THALLER et al. (2017)	Qualitative	Urban	-	Vensim	CLD
WANG et al. (2020)	China	Nation/Region	1999–2017	Vensim	✓
YORK et al. (2017)	South Africa	Nation/Region	2001–2040	Vensim	-
ZENEZINI and MARCO (2020)	Generic	Urban	100 months	Vensim	✓
ZHANG et al. (2019)	China	Urban	2018–2022	Vensim	CLD

1 The first range refers to a simulation run with historical data for validation purposes, and the second refers to future simulations. ✓ All diagrams presented; CLD *—causal loop diagram partially presented; S and F *—stock and flow diagram partially presented.

Table 2.2 summarizes the classification of the studies according to the green logistics framework, where decarbonization strategies correspond to (1) reducing freight transport demand; (2) shifting freight to lower-carbon transport modes; (3) improving assets utilization; (4) increasing energy efficiency; (5) switching to lower-carbon energy. The TIMBER framework refers to (T) technology; (I) infrastructure; (M) market; (B) behavior; (E) energy; (R) regulation, and policies related to (ECO) economic; (SOC) social; (LEG) legal; and (KNL) knowledge-based instruments.

As shown in Table 2.2, none of the studies simultaneously addressed the five decarbonization strategies. The most common decarbonization strategy for freight transport considered in the SD models is mode shift, with 15 models concerning this measure and 11 studies considering it a secondary option. Analyzing external forces, a high dependence on the infrastructure factor to implement this strategy can be observed. Social policy regarding infrastructure investments is usual among these models, although other policies are also applied, such as economic incentives, taxation, technologies, and legal requirements.

The second most common decarbonization strategy addressed by 13 SD models is alternative fuels, with the other seven models considering this measure in conjunction with different strategies. As expected, the principal external forces needed to implement this strategy are technology and energy availability, although infrastructure availability and market acceptance are also of concern. The policies simulated in the models are mostly related to economic incentives (subsidies for alternative fuels, taxes on fossil fuels, and others) and knowledge-based investments in the R&D field. Social and legal policies were also found regarding refueling/recharging infrastructure investments and obligation schemes, such as blend targets (i.e., biodiesel with diesel).

Vehicle and asset utilization appear in eight SD models, and seven studies cite this as a secondary decarbonization strategy. Behavior is the main external force supporting this strategy. It depends on the business culture and willingness to establish partnerships for sharing assets, logistics centers, warehouses, transport infrastructure, load optimization, and consolidation. Policies simulated in the SD models include economic incentives to improve efficiency and encourage companies with financial benefits. Infrastructure and technology investments, as well as legal requirements, were also considered.

Table 2.2 – Identification of decarbonization strategies, external forces, and policy instruments.

Study	**Decarbonization Strategies**[1]					**External Forces**[2]						**Policies**[3]			
	1	**2**	**3**	**4**	**5**	**T**	**I**	**M**	**B**	**E**	**R**	**ECO**	**SOC**	**LEG**	**KNL**
AGHA et al. (2019)	x[4]							x				x			
ASCHAUER (2013)		x	x				x		x			x			
ASCHAUER et al. (2015)		x	x				x		x			x			
AZLAN et al. (2019)	x	x		x		x	x					x	x		x
BARISA and ROSA (2018a)		x			x	x	x	x	x	x		x			x
BARISA and ROSA (2018b)		x			x	x	x	x	x	x	x	x	x	x	x
CAGLIANO et al. (2015a)				x	x	x	x	x	x	x		x	x		
CAGLIANO et al. (2015b)				x	x	x	x	x	x	x		x	x		
CAGLIANO et al. (2017)				x	x	x	x	x	x	x		x	x		
CHOI et al. (2019)		x				x	x		x			x	x		x
BRITO JUNIOR et al. (2011)		x					x						x		
DOLL et al. (2010)		x	x				x				x	x		x	
DONG et al. (2019)		x					x		x				x		
ERDMANN et al. (2004)	x					x		x	x						x
FIORELLO et al. (2010)		x			x	x	x			x		x	x		x
FREEMAN et al. (2015)	x			x		x				x		x			x
GENG et al. (2017)				x	x	x			x	x					x
HADDAD et al. (2019)		x			x	x	x			x		-	-	-	-
HAMOUDI et al. (2021)	x		x						x			x			x
HAN and HAYASHI (2008)		x					x				x	x	x		
HIDAYATNO et al. (2019)	x		x					x				x			
HILTY et al. (2006)	x					x		x	x						x
HU et al. (2019)		x					x		x			x	x		
HUANG et al. (2021)		x					x				x	x	x		
KAR and DATTA (2020)	x		x			x		x				x			x
KRAIL and KÜHN (2012)				x	x	x		x	x	x		x			
KUNZE et al. (2016)	x					x		x		x	x	x		x	
LEWIS et al. (2014)		x		x		x	x	x	x	x			x		x
LEWIS et al. (2015)		x		x		x	x		x				x		
LIU and MU (2015)			x				x				x		x	x	
LIU et al. (2017)		x	x	x			x				x		x	x	
LIU et al. (2019)		x	x	x			x				x		x	x	
LIU et al. (2021)		x					x						x		
MELKONYAN et al. (2020)	x		x			x		x	x				x		x
MENEZES et al. (2017)				x	x	x		x		x	x	x		x	x
OUMER et al. (2015)			x			x			x						x
PURWANTO et al. (2011)		x	x		x	x				x	x	x		x	x
ROZENTALE et al. (2020)		x			x	x	x			x			x		x
SCHADE and SCHADE (2005)	x	x	x	x	x	x	x	x	x	x	x	x	x		x
SEITZ (2014)				x	x	x	x	x		x	x	x	x		x
SEITZ and TERZIDIS (2014)				x	x	x	x	x		x			x		x
SETIAWAN et al. (2019)		x		x	x	x	x			x		-	-	-	-
SHAFIEI et al. (2014)				x	x	x	x	x		x		x			x
SIM (2017)		x	x		x	x	x			x		-	-		-
THALLER et al. (2016)	x							x				-	-	-	-
THALLER et al. (2017)	x						x	x				-	-	-	-
WANG et al. (2020)		x		x	x	x	x	x	x	x	x		x		x
YORK et al. (2017)		x					x						x		
ZENEZINI and MARCO (2020)			x		x	x			x	x		x	x		
ZHANG et al. (2019)	x						x					-	-	-	-

[1]Where 1-demand reduction; 2-mode choice; 3-assets utilization; 4-energy efficiency; 5-alternative fuels. [2]T-technology; I-infrastructure; M-market; B-behavior; E-energy; R-regulation. [3]ECO-economic; SOC-social; LEG-legal; KNL-knowledge-based instruments. [4]Shading highlights the main decarbonization strategy in the respective model.

Reducing or managing the freight transport demand is the decarbonization strategy of 10 SD models and appears in four other studies as a secondary measure. The external force that supports this strategy is market acceptance, as freight transport demand is highly related to consumption patterns and prices that will affect demand according to the price elasticities of each product category. The policies simulated are related to economic measures, increasing fees and transport costs, reducing goods and transport demand, and knowledge-based instruments, for instance, simulating the impacts that information and communication technologies will have on freight transport demand.

Lastly, four SD models presented the strategy of improving vehicle efficiency, with 14 other studies considering it secondarily. Similarly to alternative fuel promotion, the implementation of this strategy requires the availability of technology and energy as external forces. Market acceptance, infrastructure, behavior, and regulation are of minor concern in these models. Simulated policies include knowledge-based instruments with technology investment, social instruments with infrastructure investment, and economic instruments with incentives to adopt innovation and discourage old and outdated technologies.

The following subsections are related to the specific decarbonization strategies of the green logistics framework, describing the main impact on mechanisms and pathways, including how models deal with dynamics aspects.

2.3.1 Reducing Freight Transport Demand

Reducing the freight transport demand requires a range of processes to minimize the physical amount of goods to be delivered, such as material efficiency, including making products last longer, recycling, digitization, designing products with less material, and postponement of product customization (MCKINNON, 2018). Other measures can include price increases, which affect transport demand according to cost elasticity. Table 2.3 summarizes the SD models' objectives, policy elements, contributions, and limitations for reducing freight transport demand.

Table 2.3 – Contributions of the SD models for reducing freight transport demand modeling.

Authors	Objectives	Policy Elements	Contributions	Limitations
ERDMANN et al. (2004); HILTY et al. (2006)	To assess the influence that information and communication technologies (ICTs)	Investment in new technologies	ICT-related efficiency improvements are not sufficient to stabilize freight demand and other demand-side management policies	The SD diagrams were not presented. There is no discussion about time responses or other dynamics of

Authors	Objectives	Policy Elements	Contributions	Limitations
	have on environmental sustainability		are required	policy implementation and their effects
FREEMAN et al. (2015)	To examine the dynamic relationship between the consumption of goods and services, technological efficiency, and associated resource use	Investment in technological efficiency	The fleet efficiency induces travel consumption and more CO_2 emissions. Higher fleet efficiency requires costlier travel and a reduction in travel consumption	It highlighted the need to implement a system of interventions; however, no details were described regarding the dynamics of such implementations
KUNZE et al. (2016)	To generate a holistic understanding of the potential to reduce freight transport demand	Application of higher transport taxes	Identifying the reinforcement loop, since economies of scale lead to more freight demand, and the balancing loop, as higher taxes discourage the freight demand increase	The model requires further discussion, as well as validation and application
THALLER et al. (2016; 2017)	To discuss the behavioral patterns and interdependencies of relevant stakeholders in the freight transport market at an urban level	Not considered	The focus was on the decision processes and behavior of the freight demand and the freight transport demand, which affects freight traffic and the environment at an urban level	The model presents the effects of consumption patterns on freight transport demand but does not provide any policy instruments to manage or mitigate it
AGHA et al. (2019)	To model the effects of fuel price on intercity road traffic volume	Increase in fuel prices	The fuel price increase is not sufficient to reduce the transport demand due to population increase, positive economic growth, and investment in road infrastructure	The dynamics of the market response, that is, the time lag that it would take between price increase and demand reduction, was not evidenced
HIDAYATNO et al. (2019)	Relates to the total CO_2 emissions generated through urban freight volume powered by e-commerce growth	Carbon tax internalization	Development of feedback loops with general assumptions about freight transport demand variations	The model was not simulated or validated. Time lag decisions and response delays were not considered
ZHANG et al. (2019)	Determines the causal relationship between road transport and social economy, population, passenger transport, freight turnover, and energy demand	Not considered	Predictions of the freight transport demand and CO_2 emissions simulating high and low levels of oil and gas resource and technology, oil price, and economic growth	The model does not apply any decarbonization strategy, despite simulating the impact of transport demand increase over emissions
KAR and DATTA (2020)	Understanding of the relationship between product prices, fuel, number of vessels, freight, and weight value ratio	Product prices and logistic costs variation	This study shows that the cost of logistics has a significant impact on the demand for products with price elasticity greater than one	The model does not consider the dynamics of relevant policies, such as logistics collaborations, partnerships, and vertical integration

The models differ in terms of boundary delimitations, inputs, and outputs. Consequently, distinct structures of causal loop diagrams or stock and flow diagrams were found according to their goals. ERDMANN et al. (2004) and HILTY et al. (2006) assessed the rebound effects of efficiency gained with information and communication technologies over freight demand stimulation, which counterbalances or even outweighs positive environmental benefits.

As people get used to traveling more and having access to more goods due to gross domestic product (GDP) improvement, the social norm increases, influencing travel and consumption in a reinforcement feedback loop (FREEMAN et al., 2015). Moreover, as fleet efficiency increases, travel costs decrease, leading to a rebound effect on transport demand. On the other hand, road congestion limits the growth in transport demand. A high volume of urban transport will lead to more traffic and reduce environmental quality (KUNZE et al., 2016). It would require legal regulations (e.g., higher taxes) to reduce transport demand. On the other hand, if the freight transport volume is high, the efficiency of logistics operations is likely to grow, improving economic performance and increasing freight transport demand.

THALLER et al. (2016; 2017) modeled the interdependencies of relevant stakeholders in the freight transport market. The main focus was on decision processes regarding freight demand (e.g., private households, retailers, and shippers) and the resulting freight transport demand of the logistics service provider, which affects freight transport volume, traffic, and environmental problems at an urban level. According to AGHA et al. (2019), the increase in fuel price affects per capita income, thereby reducing vehicle purchases. However, due to population increase, positive economic growth, and annual investment in road infrastructure, changes in the fuel price are not sufficient to reduce transport demand.

According to HIDAYATNO et al. (2019), CO_2 emissions are related to the urban freight volume powered by e-commerce. Their assumptions show that the urban freight volume will directly influence GDP, leading to higher product consumption, and e-commerce orders will likely increase, affecting urban freight volume in a reinforcing feedback loop. These factors will induce greater energy consumption and CO_2 emissions, increasing urban logistics transport costs through the internalization of a carbon tax, resulting in a demand decrease.

The GDP increases transport investment, which will decrease traffic congestion, energy consumption, and emissions, leading to an improvement in GDP (ZHANG et al., 2019).

Moreover, the increasing population will decrease GDP per capita, reducing the number of private cars, traffic volume, energy consumption, and emissions. It was also assumed that population growth would increase the use of non-motorized travel (ZHANG et al., 2019), which is debatable since slow modes depend on land use and suitable infrastructure. KAR and DATTA (2020) assessed the dynamics between product prices and freight demand. The authors argued that the mark-up variation might further lead to an increase or decrease in prices, causing an inverse effect on product demand, which is also influenced by logistics costs.

Despite the differences found in the presented literature, some usual variables and assumptions can be highlighted regarding the dynamic relationships in freight transport demand modeling that form the feedback loops in Figure 2.3. In a summarized form, emissions are affected directly by fleet efficiency and fuel consumption. Fleet efficiency depends on environmental regulations balancing freight emissions. However, fuel consumption varies according to transport demand, which is affected by other feedback loops, including those with delay effects.

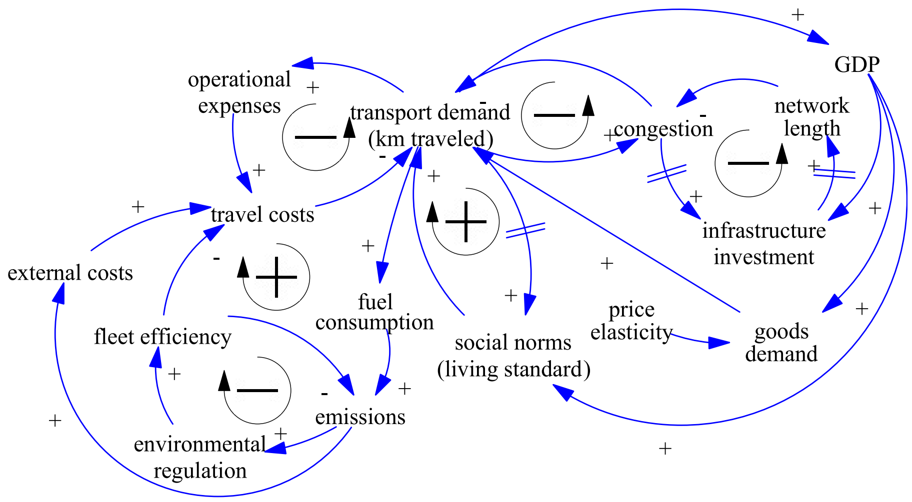

Figure 2.3 – Common dynamic relationships in freight transport demand modeling.
Source: based on AGHA et al. (2019); FREEMAN et al. (2015); HIDAYATNO et al. (2019); KAR and DATTA (2020); THALLER et al. (2016; 2017); ZHANG et al. (2019).

Regarding the quantitative and simulation aspects, most of the studies did not present the model equations, except for ZHANG et al. (2019), which makes it challenging to analyze, replicate, or apply the models. Moreover, there is no information about integration techniques or time steps used. Another difficulty is the identification of delays. Although some delays are represented in the diagrams (arrows with hash marks), their estimations were not provided. Other relevant measures, such as the internalization of emission costs, are supposed to take some time to be implemented; however, their delays were not even pointed out in the diagrams. The discussion about time responses, an essential dynamic aspect, requires better exploration.

2.3.2 Shifting Freight to Lower-Carbon Transport Modes

It is important to increase the performance of railway, waterway, and combined multimodal transport in terms of the comparable price, quality, service, and flexibility of roadway transport to increase the use of alternative modes. Using synchromodality that focuses on the optimal and flexible use of multiple modes is expected to contribute to this solution area (ALLIANCE FOR LOGISTICS INNOVATION THROUGH COLLABORATION IN EUROPE – ALICE, 2019). Table 2.4 summarizes the SD models' objectives, policy elements, contributions, and limitations for shifting mode modeling.

Table 2.4 – Contributions of SD models for shifting freight to low-carbon mode modeling.

Authors	Objectives	Policy Elements	Contributions	Limitations
SCHADE and SCHADE (2005)	To model the economic, transport, environmental, and policy aspects that describe a path toward a sustainable transport system and its economic impacts	Higher transport prices (taxes); investment in alternative modes; investment in energy efficiency and alternative fuels	The growth of freight transport tends to be absorbed by rail and ship transport since these modes are attractive enough	The high aggregation level and the absence of the model feedback loops and related dynamics make it challenging to analyze the considered assumptions
HAN and HAYASHI (2008)	To assess the CO_2 emissions from an intercity freight transport considering the modal share, the freight volume, fuel price, and fuel intensity	Extension of the railway and waterway network and imposition of fuel taxes	Policies simulated are very significant for CO_2 emissions mitigation	Dynamics of changes in the system were not provided, compromising the interactions between policies, mode choice, and emissions mitigation discussion
BRITO JUNIOR et al. (2011)	To analyze the causal relationships influencing the modal shift from road to coastal shipping	Investment in infrastructure capacities and governmental pressure to reduce CO_2 emissions	Results show that the inertia for the modal shift is long	It was not evidenced how the pressure to reduce CO_2 emissions and shift modes was quantified. Other factors were not considered by the model, such as pricing policies, tax incentives, and subsidies to shift modes
LEWIS et al. (2014; 2015)	To explore the strategies for greenhouse gas (GHG) emission reductions, with a specific focus on the mode switch from road to rail	Increasing the fuel price, electricity price, carbon tax; investment in rail infrastructure; fleet efficiency	Existence of different decision-making behaviors to adopt innovations, depending on the type and size of companies	The congestion and capacity constraints were not considered, as well as the assumptions related to time responses

Authors	Objectives	Policy Elements	Contributions	Limitations
YORK et al. (2017)	To investigate the infrastructure implications of a green economy transition for a modal shift from road to rail	Increasing investments in the rail network	The benefits obtained include the reduction in trucks using the road network, better pavement conditions, and road safety. Such a transition would require significant investment in the rail track	It was not discussed how the modal shift would be implemented by companies over time
AZLAN et al. (2019)	To propose an SD model for emission analysis of intercity highways, including both passenger and freight transport	Increasing fuel prices, promoting alternative modes, such as railway, and educating drivers to plan their routes and schedules	The results showed a reduction in total CO_2 emissions with the policy's implementation	The model does not show the feedback loops. There is no mention of time lags regarding mode choice changes, or the adoption of intelligent systems for route planning, compromising policy evaluations
CHOI et al. (2019)	Develop an SD model to examine the impact of policies of modal shift from road to rail	Increasing road costs or taxation and containerization	Results confirmed that the modal shift by containerization occurred more rapidly than by all kinds of road taxation	Warehousing and information costs of transshipment were excluded. Dynamics were not analyzed
DONG et al. (2019)	To analyze the quantitative relationship between the mode shift from road to rail and the sustainability of urban logistics	Investment in railway infrastructure construction	The high-density development of the rail network will achieve the best indicators of performance (average speed, congestion loss, delivery travel time, and emissions)	Lack of detailed analysis of the network construction time, the secondary benefits, such as land appreciation and road safety, as well as the cost-benefit analysis for the construction of the rail network
LIU et al. (2017; 2019; 2021)	Evaluate alternative modal shift policies to eliminate overloaded trucking and increase sustainability	Legal weight regulation and investment in railway infrastructure	The weight regulation causes a higher total cost. Constructing a railway to shift freight away from highways is an effective option to achieve increasing sustainability	Some delays are assumed for model simplification without suitable discussion. Policies and their effects are fixed throughout the simulation period, which is unrealistic
HU et al. (2019)	To simulate logistics activities integrated into urban passenger rail transit networks	Different levels of infrastructure investment policy, network scale, and market competitiveness through price adjustments	The urban freight railway significantly decelerates the growth trend of external costs. However, due to the limited capacity of the system and the ever-growing urban demand, it is not sufficient to mitigate all externalities	Lack of analysis of multimodal transport system, reduction in truck damage to roads, and the benefits of land conservation, as well as the dynamics related to the policies simulated
WANG et al. (2020)	To explore transport decarbonization considering economic, social, environmental, and transportation elements	Increase the use of alternative modes and optimize energy consumption through technological innovations	The results indicate that the mode shift is the most significant measure to reduce emissions	Dynamics for mode shift, such as company change requirements and time-lag responses, were not taken into account

Authors	Objectives	Policy Elements	Contributions	Limitations
HUANG et al. (2021)	Simulate the mode shift from road to rail by levying carbon emission taxes	Increasing carbon taxes and investments in the railway network	The policies investigated have a good effect on reducing carbon emissions in the transportation industry	The model does not consider important factors to the mode choice process and the time lag for the mode shift, although it does not occur instantaneously

Analyzing the SD diagrams of the models regarding shifting freight to lower-carbon transport modes, their boundaries, variables, and interrelations that form the feedback loops or stock and flow structures can be identified.

The system dynamics model for economic assessment of sustainability policies of transport (ESCOT) was developed by SCHADE and SCHADE (2005) to assess the economic impacts of a sustainable transport system, considering macroeconomic, regional economic, transport, environmental, and policy aspects. The SD diagrams were not provided, but the results show that the growth of freight transport tends to be absorbed by rail and ship transport since these alternative modes are attractive enough.

HAN and HAYASHI (2008) evaluated CO_2 emissions, considering factors that affect the modal share, such as freight volume, network length, fuel price, and fuel intensity. However, no information regarding the dynamics of changes in the system was provided, compromising the interactions between policies, mode choice, and emission mitigation discussions. Additionally, the modal share modeling does not consider the mode's capacity and its influence on the mode choice.

BRITO JUNIOR et al. (2011) analyzed the modal shift process, driven by investment in the modes' capacities. As the mode shift increases demand, it was assumed that increasing the competitiveness of the mode used would reinforce the mode shift. According to the authors, the inertia for the modal change is long; however, it was not evidenced how the pressure and policies to shift modes were quantified. The time to promote modal shift is randomly assumed as two years. However, its endogenous impact was not demonstrated, thus raising the question of how fast other decisions and actions must occur to achieve a good balance of modal share.

LEWIS et al. (2014) explored strategies for emission reductions and determined the barriers to the mode switch, taking into account company types, decision-making behavior, generalized cost by mode, reliability, functionality, dynamic fleet model, and bands of high-, medium-, and low-cost interventions. The model was then applied and the results show that there is more perception of reliability than cost changes (LEWIS et al., 2015). The relationship between price and mode shift is not linear, capturing different companies' responses, including their tolerance of cost increases, the time lag to implement the mode shift due to contractual considerations, and the need for implementing new systems.

YORK et al. (2017) simulated the modal shift from road to rail through increased investments in the rail network. The benefits of this shift would include the reduction in trucks using the road network, better pavement conditions, and road safety. Such a transition would require significant investment to upgrade and maintain the rail track. The dynamic relationships could not be analyzed, since the SD diagrams were not provided.

AZLAN et al. (2019) analyzed the emissions from the vehicle fleet on intercity highways. The scenario devoted to freight was to reduce vehicle kilometers traveled by increasing fuel price, promoting mode shift, and educating drivers to plan their routes and schedules. Therefore, this study does not provide the impact of the isolated freight scenario in freight transport demand reduction and emissions mitigation. The model description does not show the feedback loops described, and there is no clear relation between the fuel price and the average distance traveled. Moreover, it is not clear how assumptions or time lags for mode shift and route planning were designed, compromising policy evaluations.

The impact of policy measures on promoting the modal shift from road to rail, such as the increased road cost and containerization, was also examined (CHOI et al., 2019). Increases in the imposition of taxes generally cause an increase in the total logistics cost of road transport. In contrast, containerization causes a decrease in the entire logistics cost of intermodal transport. The rate to implement the policy measures was not provided, but the results showed that the modal shift by containerization occurred more rapidly than by all kinds of road taxation.

The mode shift and sustainability of urban transportation were analyzed by DONG et al. (2019). The model assumes that the increasing economy leads to more freight volume, truck trips, and vehicle kilometers traveled, which increases congestion, delivery travel time, and emissions, all impacting economic development. However, the increasing economy also leads to more rail investments; then, the truck trip is reduced together with vehicle kilometers traveled, congestion, delivery travel time, and emissions, resulting in better economic development. The results show that the high-density development of the rail network leads to the best performance of urban transport sustainability.

LIU et al. (2017; 2019; 2021) evaluated modal shift policies to eliminate overloaded trucking. According to the initial modal share, the freight volume by mode is converted into the modal traffic, impacting congestion levels and transport time and determining the next modal split. The results show that the modal shift increases sustainability. However, the reduced freight volume of highway systems would make highway carriers react, e.g., by reducing trucking prices to compete with railway transport. Further studies could address the gaming processes of multiple stakeholders.

HU et al. (2019) simulated logistics activities integrated into passenger rail networks. The growth of the rail network improves its competitiveness and market share. External benefits stimulate more investment and subsidies, which accelerate the modal shift. On the other hand, negative impacts, such as job reductions and decreases in fuel tax revenue, decrease investments. Although dynamics have not been analyzed, the results show that the railway system mitigates emission costs.

WANG et al. (2020) explored the decarbonization goal, considering that economic development increases transportation demand and provides funds for infrastructure construction. The gap between supply and demand restricts the economic level, leading to more infrastructure investments and increasing transport supply. It was also assumed that economic development guarantees technological investment, improves transportation efficiency, and reduces energy consumption using alternative modes and technological innovations. The results indicate that the mode shift is the most significant measure, although time lags were not taken into account.

HUANG et al. (2021) simulated the mode shift by levying taxes on carbon emissions. The increasing economy leads the government to invest in railway freight transport. The government also imposes a carbon tax based on CO_2 emissions, encouraging the modal shift, and promoting the demand and growth of railway freight transport revenue, thereby raising the economy level and reducing road transport demand and CO_2 emissions. The policies investigated have a positive effect on reducing emissions; however, exceeding the carbon levy rate will cause the transfer of short-distance trips from road to rail. This result indicates that the model could be improved by considering other relevant factors, such as trip distance and freight flow. Moreover, no time lag was mentioned for the mode shift, although the companies' resistance, time for adaptation, and inertia play a role in the mode choice process.

Despite the differences presented in the literature, some common variables and feedback loops that rule the dynamic relationships in shifting freight to lower-carbon transport modes can be highlighted, as shown in Figure 2.4. In this case, emissions and fuel consumption depend on the mode used, according to the modal share. Factors influencing modal share include logistics costs, freight volume, and mode competitiveness. Economic development and pressure to reduce emissions also play a role in the feedback loops.

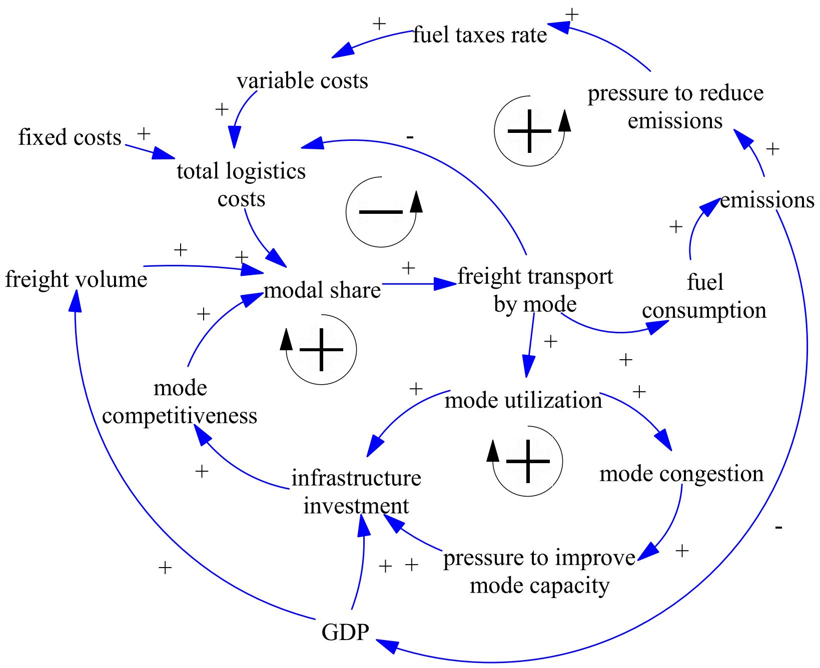

Figure 2.4 – Common dynamic relationships in shifting freight to lower-carbon transport modes.
Source: based on CHOI et al. (2019); BRITO JUNIOR et al. (2011); DONG et al. (2019); HAN and HAYASHI (2008); HU et al. (2019); HUANG et al. (2021); LEWIS et al. (2014); LIU et al. (2021); WANG et al. (2020).

Some studies only presented the main equations (not detailed) of their models (AZLAN et al., 2019; CHOI et al., 2019; BRITO JUNIOR et al., 2011; ERDMANN et al., 2004; HU et al., 2019; HUANG et al., 2021; LIU et al., 2017; 2019; 2021; WANG et al., 2020), making it challenging to analyze, replicate, or apply them. Moreover, there is no information about integration techniques or time steps used. Regarding the delays, no information was found; despite pressure to reduce emissions, the pressure to improve mode capacity, infrastructure investment, and fuel taxes may take time to be implemented. A general lack of discussion about the dynamic aspect of policy impacts in all mode choice SD models was found, i.e., how quickly or slowly the systems may change over time to achieve the results in a specific time.

2.3.3 Improving Assets Utilization

Optimizing assets utilization accommodates more freight transport demand with the same infrastructure and capital investment. It can be achieved through load optimization and consolidation, asset sharing, and better management of logistics centers, warehouses, and transport infrastructure. Transport predictability and flexibility are important enablers for this solutions area (ALICE, 2019). Table 2.5 summarizes the SD models' objectives, policy elements, contributions, and limitations for improving vehicle utilization modeling.

Table 2.5 – Contributions of SD models for improving vehicle utilization modeling.

Authors	Objectives	Policy Elements	Contributions	Limitations
DOLL et al. (2010)	To evaluate the impacts of longer and heavier vehicles on emissions and show the effect of road pricing on the market share of these vehicles compared to rail	Internalization of transport external costs; allowance of heavier trucks	Increased truck sizes and high road user charges can only limit truck traffic growth for a specific time. The negative impacts in the medium term are much stronger than the initial positive effects	It was not analyzed how different types of companies react to the internalization of external costs and how they decide to use railway or heavier trucks
ASCHAUER (2013); ASCHAUER et al. (2015)	To model the interdependencies between logistics strategies and transportation with the goal of higher utilization of trucks and a modal shift to rail	Growth of transport costs through internalization leads to more pressure to consolidate freight	The model concentrates on operative parameters, such as order cycle frequency, amount per order cycle, and shipment amounts	Inventory costs were disregarded, although this could lead to different results
OUMER et al. (2015)	To simulate CO_2 emissions for inbound and outbound logistics in an automotive assembly line	Shipment consolidation	Unlike the majority of SD models, this study addressed operational activities at a company level	How the policy will be implemented and the time response of its effects was not presented
LIU and MU (2015)	To evaluate the effects of alternative truck weight regulation policies on the sustainability of a highway freight system	Alternative weight regulation policies	Social costs, such as pavement maintenance, traffic accidents, and emissions, are simulated, evidencing the sustainability of different weight regulations	Consideration of a single freight and truck type while neglecting the storage process. Delays were simplified, as the pavement maintenance was assumed to occur within the model time step

Authors	Objectives	Policy Elements	Contributions	Limitations
SIM (2017)	To analyze the carbon emission abatement required for the truck freight sector while investigating the uncertainty in demand and technology developments	Not considered	It simulates the total emission reduction target, and the result is the percentage of reduction needed in the transport sector. Policies are recommended but not simulated	Despite freight volume and carbon emissions target changing dynamically, the discussion about how this change occurs over time was not provided
MELKONYAN et al. (2020)	To explore the sustainability potential of last-mile logistics and distribution strategies, employing different delivery alternatives	Investments in digital applications for tracking and tracing and outsourcing the pickup to consumers	The crowd logistics concept (in which the logistics service provider decides where to pick up the parcel or whether to outsource the pickup to individuals) is the better solution	Significant factors were not applied, such as carbon taxation, inventory management, and economic parameters
HAMOUDI et al. (2021)	To analyze the freight flows in a distribution chain based on inventory and transport costs and the evolution of the customer order	Internalization of CO_2 emissions tax; different levels of truck capacity utilization	Logistic decisions are taken at the supply chain level, as the loading vehicles' rate, their loading capacity, their order cycle frequency decisions are generally taken lightly in the companies, whereas they influence the distribution costs, transport demand, fuel consumption, and emissions	The model disregarded relevant market parameters, such as financial aspects, marketing strategies to make the business greener, and others

Different assumptions can be identified by analyzing the SD diagrams of the models, their variables, feedback loops, and stock and flow structures. DOLL et al. (2010) evaluated the impacts of longer, heavier vehicles (LHVs) on emissions. For the market entry of LHVs, adaptation processes in logistics sectors have to take place. An unavoidable delay between legal permission and full market penetration occurs. This delay is longer for railways since more complex logistics processes must be refined. The results show that depending on the rail freight demand and costs by transport unit, the modal shift may take place from rail to road, undermining CO_2 reduction gains. However, the discussed delays for the logistics adaptation process were not estimated.

ASCHAUER (2013) and ASCHAUER et al. (2015) modeled logistics strategies toward more efficient transport operations and higher utilization of trucks. The shipment amount is influenced by the operating logistics concept (i.e., just in time), which affects the order cycle frequency and the amount per order cycle. Small shipment amount means a low utilization of trucks, which influences the transport distances traveled, fuel consumption, emissions, transportation costs, and the pressure to consolidate. If consolidation pressure increases, the shipment amount also increases, which takes time, as companies have to identify consolidation potential. This response time has to be further explored.

CO_2 emissions for inbound and outbound logistics based on shipment consolidation technique in an automotive assembly line were simulated by OUMER et al. (2015). CO_2 emissions were calculated based on the total number of trips made by inbound and outbound transport vehicles and the type of fuel used. However, the shipment consolidation policy and the assumptions about how it should be implemented (i.e., increasing load factor and vehicle capacity) were not presented.

The effects of alternative truck weight regulation policies on the sustainability of a highway freight system, considering economic and social costs including pavement maintenance, traffic accidents, and emissions, were evaluated by LIU and MU (2015). Three levels of weight regulation policies were considered. The best policy varies according to the importance of social costs. The model presents neither the SD diagrams nor the equations, delays, or time lags between policy implementation and results.

SIM (2017) considered that an increase in the truck–freight demand increases emissions, which are estimated based on the total transportation volume of each truck type (light, medium, and heavy) and the carbon density over the traveled distance. The freight volume and carbon emissions target are time-dependent, but the discussion about how the change occurs over time was not provided. The results suggested increasing the use of medium and heavy trucks. Further exploration of whether large or heavy trucks can replace light trucks is necessary.

MELKONYAN et al. (2020) explored the sustainability of last-mile logistics with different distribution strategies. The centralized distribution case is profitable due to increased demand, while the operational and environmental costs increase. In the home delivery case, the emissions will be more significant, given a substantial increase in customers, increased transport distances, and a higher truck emission rate. The distributed network system considered crowd logistics operations relying on a sharing economy model, in which pollution will not increase sharply compared to previous options. The time that companies take to change their distribution strategies should be further explored.

HAMOUDI et al. (2021) analyzed freight flows in a distribution chain based on inventory and transport costs. The logistics decisions are taken at the supply chain level, as the choice of loading vehicle rates and order cycle frequency is generally taken lightly by the companies, whereas they influence distribution costs, transport demand, fuel consumption, and emissions. Low truck utilization involves a high number of shipments, which increases road use, reduces average speed, and increases lead time and transport costs, impacting customer satisfaction, demand, and order quantity per year.

Figure 2.5 presents the usual variables and feedback loops that rule the dynamic relationships in the models related to the improvement of asset utilization. The logistics concept of the supply chain dictating the order cycle frequency and amount per order cycle, the distribution costs impacting customer satisfaction and demand, and the pressure to consolidate are some of the key variables forming the feedback loops. Fuel consumption and emissions are influenced by the distance traveled, which depends on vehicle utilization.

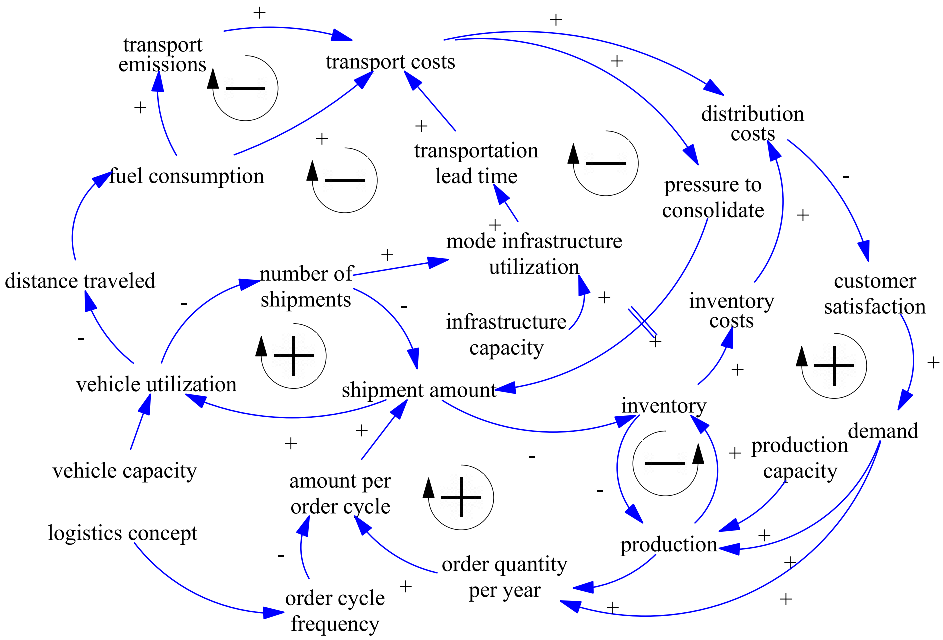

Figure 2.5 – Common dynamic relationships in improving asset utilization models.
Source: based on ASCHAUER (2013); HAMOUDI et al. (2021); MELKONYAN et al. (2020); SIM (2017).

Regarding the quantitative phase of the SD models, ASCHAUER et al. (2015) and MELKONYAN et al. (2020) presented the model equations in detail, and LIU and MU (2015) and SIM (2017) presented some main equations, while the other studies did not provide them, showing a lack of transparency. Integration techniques or time steps used were not revealed. The only delay reported (but not quantified) was between the pressure to consolidate and the shipment amount. In contrast, uncertainties may exist related, for example, to customer satisfaction and the influence of emissions on transport costs, which requires the internalization of external cost processes. Such dynamic aspects should be further investigated.

2.3.4 *Increasing Energy Efficiency*

Increasing vehicle efficiency involves using cleaner and more efficient technologies, fleet renewal, and driving behavior/eco-driving, among other measures. An increase in the variety of technologies reducing CO_2 emissions in heavy commercial vehicles is expected; however, this market implies multiple stakeholders, which considerably affects market dynamics. Table 2.6 summarizes the SD models' objectives, policy elements, contributions, and limitations for increasing energy efficiency modeling.

Table 2.6 – Contributions of SD models for increasing energy efficiency modeling.

Authors	Objectives	Policy Elements	Contributions	Limitations
KRAIL and KÜHN (2012)	To simulate the diffusion of alternative fuels and show the potential of fuel efficiency technologies for conventional vehicles	Taxes on different technologies and emissions levels	Hydrogen is considered a promising technology for long-distance and regional traffic, while light distribution traffic is predestined for electric drives	Other factors (technical attributes, range, recharging time, and refueling/recharging stations density) that influence market adoption of new technologies were not considered
SEITZ (2014)	To analyze the diffusion of technologies reducing CO_2 emissions in heavy commercial vehicles	Investments in refueling infrastructure and R&D technologies	The factors for the successful diffusion of CO_2-saving technologies were discussed from a stakeholder perspective	The framework was not quantified, applied, and validated
SEITZ and TERZIDIS (2014)	To forecast the market penetration of alternative powertrain technologies to the heavy commercial vehicles market	Investment in refueling stations and R&D for alternative powertrains. Costs of adoption and ownership are taken into account	The model is helpful to study some market dynamics and highlight the sensitive factors of the market diffusion process	The missing empirical data compromise the analysis of market diffusion
GENG et al. (2017)	To interrelate regional ship emissions, economic growth, and the development of a sustainable ecosystem	Speed reduction, use of shore electricity, engine improvement, and exhaust after-treatment technologies	The model provides assumptions that determine the model behavior. Ship speed should be optimized to achieve greater benefits	There is a lack of reasonable validation and uncertainties in the variable equations and parameter values

Analyzing the SD diagrams of the models related to increasing energy efficiency and their variables, feedback loops, and stock and flow structures, we can identify different assumptions made to model the system under study. KRAIL and KÜHN (2012) simulated the diffusion of alternative fuels and drives within the truck market. There is a common link between the cost of trucks and their adoption, influencing the manufacturing costs via economies of scale. Investing in new technology is driven by economic forces considering the investment, maintenance, fuel, toll, taxes, and refueling costs.

SEITZ (2014) also analyzed the diffusion of technologies reducing CO_2 emissions in heavy commercial vehicles. The study identified that customer preferences change with gaining market shares of innovative technologies. Therefore, the adoption decision impacts the organization by influencing the social network, supplier's efforts, governmental regulation, and the energy supply system. The causal loop diagram presents delays between some variables, such as governmental regulation, station construction, and market share, although they are not adequately discussed in the study.

SEITZ and TERZIDIS (2014) modeled the penetration of alternative powertrain technologies into the heavy commercial vehicles market. The model presented some market dynamics and highlighted the sensitive factors of the diffusion process. However, there are several limitations due to missing dynamic empirical data.

GENG et al. (2017) interrelated regional ship emissions, economic growth, and sustainable ecosystem development. Although the causal loop descriptions do not characterize feedback loops, the model provides assumptions that determine its behavior, divided into five sub-systems: shipping, energy, environment, economic, and policy components. The results show that ship speed should be suitably reduced to achieve more significant economic and environmental benefits. The model's limitations include a lack of proper validation and uncertainties in the variable equations and parameter values.

Figure 2.6 presents the common variables and feedback loops that rule the dynamic relationships in the models related to increasing energy efficiency. R&D investment, influenced by both manufacturer interests and pressure to reduce emissions, increases vehicle efficiency and reduces emissions. The attractiveness of CO_2-saving technologies considers different factors, such as technology costs, consumer familiarity, refueling station coverage, and fuel prices.

In the quantitative phase of the SD models, only SEITZ (2014) did not provide the equations, while the other studies provided some of them. Moreover, there is no information about integration techniques or time steps used. The diagrams represent some delays, although their estimations were not provided. Decisions related to the fleet renewal process and adoption of alternative technologies may take significant time to better investigate in future SD models.

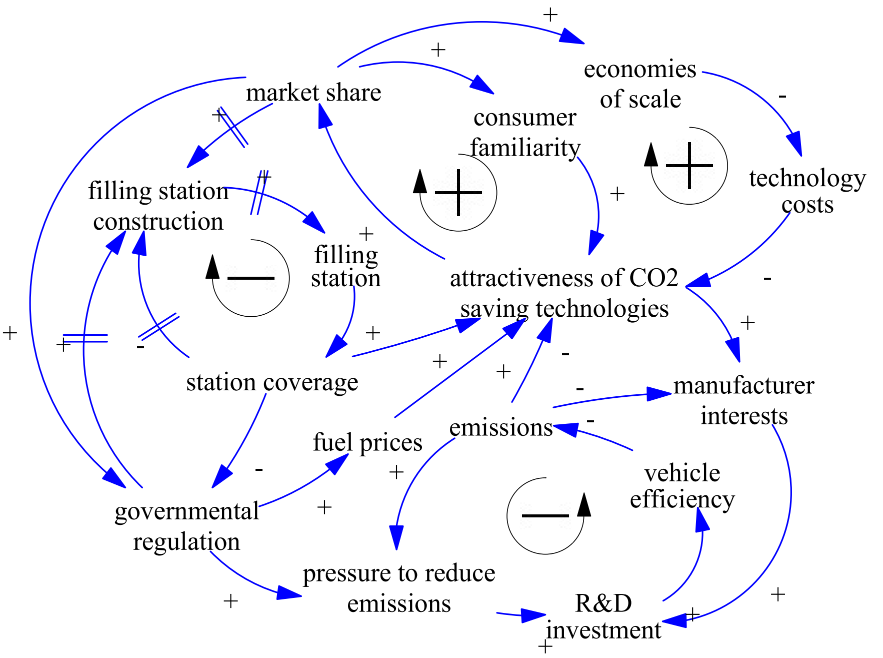

Figure 2.6 – Common dynamic relationships of increasing energy efficiency models.
Source: based on GENG et al. (2017); SEITZ (2014); SEITZ and TERZIDIS (2014).

2.3.5 *Switching to Lower-Carbon Energy*

Achieving deep carbon reductions will require a significant shift from fossil fuels to renewable energy. In this solution area, the focus is on reducing the carbon content of energy sources. The available options include using cleaner and lower-carbon fuels, such as biofuels, blended fuels, hydrogen, and electrification that ideally uses renewable energy, whose adoption will have significant challenges related to politics, economics, collaboration, awareness of technologies and methods, investment in renewable energy, acceptance of new technologies by societies, and type of governance (RAZMJOO et al., 2022). Table 2.7 summarizes the SD models' objectives, policy elements, contributions, and limitations for promoting alternative energy sources.

Different assumptions were identified by analyzing the SD diagrams, their variables, feedback loops, and stock and flow structures. FIORELLO et al. (2010) presented the assessment of transport strategies (ASTRA) model to assess energy scarcity, high oil prices, and technological investments in the transport sector, besides simulating transport taxation, infrastructure investments, incentives to accelerate fleet renewal, and increases in fuel prices. The typical results are projections of transport demand, CO_2 emissions, and the evolution of vehicle fleets. However, the model structure is not presented; therefore, it is impossible to analyze its structure and feedback loops.

Table 2.7 – Contributions of SD models for promoting alternative energy sources modeling.

Authors	Objectives	Policy Elements	Contributions	Limitations
FIORELLO et al. (2010)	To assess policies concerning energy scarcity, high oil prices, and technological investments in the transport sector	Transport taxation, road charging, infrastructure investments, incentives for fleet renewal, and increases in fuel resource prices	Analysis of transport demand, CO_2 emissions, and evolution of vehicle fleet. Simulation of transport at the strategic level	The model was not presented; therefore, it was not possible to analyze its structure and feedback loops in detail, compromising its replicability
PURWANTO et al. (2011)	To estimate transport demand emissions and impacts of policy and technological measures covering all transport modes from the different regions in the world up to 2050	New emission standards, penetration of alternative technologies, an increase in fuel efficiency, and fleet renewal; fuel quality; incentives for low-emission cars, internalization of external costs; and traffic management	Useful for transport, environmental, and economic analysis of different policies and measures to reduce emissions from transport	Only the structural components of the model in a macro-overview are provided, while the SD diagrams are dismissed, compromising the replication of the model or the evaluation of the feedback loops and the model dynamics
SHAFIEI et al. (2014)	To model interactions between the energy supply sector and road transport energy demand	Oil price variations, alternative fuel availability, and carbon taxes	Rising fossil fuel prices, carbon tax, and initial investment in alternative fuel supply could reduce emissions; however, more stringent policies will be necessary for a carbon-neutral scenario	The model does not consider the performance deterioration of battery and fuel cells. It also lacks an analysis of the costs of refueling and recharging infrastructure
CAGLIANO et al. (2015a; 2015b; 2017)	To assess the diffusion of a city logistics system based on electric and hybrid vehicles	Subsidies for alternative technologies and investment in refueling/ recharging infrastructure	Advertising campaigns, involvement of public authorities, and adoption of suitable technologies are the main aspects that can stimulate the diffusion of alternative vehicles	The dynamic process of adoption of technologies by companies is not presented, as well as the assumptions made about time responses to policy implementation
MENEZES et al. (2017)	To evaluate low-carbon urban development strategies for the transport sector	Improving fuel efficiency and promoting the use of biofuels	The policies simulated are not enough to achieve the required emissions reduction. Efficiency gains should be combined with measures to reduce the rebound	The model does not consider other decarbonization strategies that may be impactful in the long run, as well as a cost-benefit analysis of the policy mix

Authors	Objectives	Policy Elements	Contributions	Limitations
			effect on travel demand	
HADDAD et al. (2019)	To estimate the potential reductions in fuel use and CO_2 emissions from electrified truck technologies, combined with using electric rail for heavy freight transport	Not considered	The strategies simulated lead to a reduction in energy use and corresponding emissions but are not enough to reverse current growth trends	The model does not evidence of how strategies should be implemented (policies) and what the related dynamics involved are
BARISA AND ROSA (2018a; 2018b)	To forecast emissions from transport sub-sectors in response to changes in social, economic, technical, and policy aspects	Fossil fuel taxes, subsidies for alternative fuel vehicles, investment in refueling/ recharging infrastructure, mandatory use of biofuels, increase in environmental awareness, and efficiency improvement	The results confirm that there is no single policy instrument that could reduce GHG significantly, and a broad portfolio of policy measures is needed	The model was only partially presented; thus, it was not possible to evaluate the model structures and the assumptions made for the system's dynamic behavior over time
SETIAWAN et al. (2019)	To analyze energy consumption and CO_2 emission reductions from the road transportation sector	Efficiency improvements, mode shift from truck to rail, and adoption of electric vehicles	If adopting one single policy, electric vehicle adoption produces better results; however, the optimal result should include a mix of policies to achieve further emission reductions	The paper does not provide the feedback loop descriptions and does not mention the assumptions made regarding the time responses from the policy's implementation to the result's achievement
ROZENTALE et al. (2020)	To evaluate the electrification of the railway considering the electrical supply system and its development, power demand, economic, and environmental effects	Investment in railways and new energy sources	The electrification of railways has considerable potential to reduce emissions from the freight transport sector, helping to achieve climate targets	The policy is assumed to be implemented by 2030; however, the actions needed and the time they will take have not been discussed
ZENEZINI and MARCO (2020)	To grasp the complexities inherent to the city logistics system, the policy-making process, and its connections to operational and economic variables	Road infrastructure capacity; load consolidation; economic incentives for electric vehicles	As green vehicles are assumed to be more attractive, they absorb the increase in demand, starting a transition from traditional to green vehicles	The model does not consider green technologies other than electric vehicles, as well as other factors that impact their adoption, such as technical issues and market acceptance dynamics

PURWANTO et al. (2011) presented the global scale system dynamic simulation model for transport emissions (GLADYSTE) to estimate the impacts of policy and technological measures in transport-related sectors. The scenarios include new technologies, fuel quality, fiscal instruments, and traffic management policies. However, the SD diagrams and equations were not provided, making it unfeasible to replicate the model and evaluate the behavior or the assumptions between variables and the feedback loops, delay equations, or time-related variables.

SHAFIEI et al. (2014) modeled the interdependencies between the energy supply sector and road transport energy demand. The findings show that rising fossil fuel prices, carbon taxes, and investing in alternative fuel supply could reduce emissions. However, more stringent policies will be necessary for a carbon-neutral scenario, such as efficiency improvements, travel demand management, vehicle technology shifts, and fuel switches.

CAGLIANO et al. (2015a; 2015b; 2017) modeled the diffusion of a city logistics system based on electric and hybrid vehicles. The size of the fleet depends on freight demand, vehicle capacity, and load factor. The lower operating costs of alternative technologies generate savings and reinforce their adoption. However, the greater the number of vehicles, the more investment is needed, negatively affecting their purchase.

MENEZES et al. (2017) evaluated low-carbon strategies for the transport sector by using the SD model For Future Inland Transport Systems (ForFITS). This model estimates the demand for each transport mode based on GDP, population, economic growth, price inflation, and other analyses. Policies adopted for freight transport include improving fuel efficiency and promoting the use of biofuels. The substitution of less efficient vehicles may occur slowly over time, although such delay was not addressed.

HADDAD et al. (2019) also employed ForFITS to estimate fuel use and emission reductions from electrified trucks and electric railways. Increasing the share of plug-in hybrid electric and fully electric trucks would reduce energy use and emissions, but it would not be enough to reverse current demand growth trends. Increasing the share of rail transport would lead to an additional reduction while combining both mitigation options indicates the highest savings. This solution comes at the cost of providing the necessary electric charging infrastructure and clean energy mix to operate these vehicles effectively, which may not occur as quickly as desired.

BARISA and ROSA (2018a; 2018b) analyzed CO_2 emission mitigation in the road transport sector in response to social, economic, technical, and policy changes. Fuel consumption depends on fuel type, vehicle type, and distance traveled, while CO_2 emissions depend on fuel consumed and emission factors. No single policy instrument could reduce emissions significantly, and a broad portfolio of policy measures is needed. SD diagrams were not provided, making it difficult to evaluate model structures and the assumptions made for the system's dynamic behavior over time.

SETIAWAN et al. (2019) analyzed the road transportation sector's energy consumption and CO_2 emission reduction. Policies simulated fuel economy standards through efficiency improvements, mode shift from road to rail, and adoption of electric vehicles. Electric vehicle adoption is a good alternative, although the optimal result should include a mix of policies to reduce emissions. The paper does not provide the feedback loop descriptions and does not mention the assumptions made regarding the time responses from policy implementation to the result's achievement.

ROZENTALE et al. (2020) evaluated the impact of the railway electrification system. One dynamic factor included in the model is financial stability, which is very difficult to achieve, as railway operations require a lot of resources and an even flow of transport. At the beginning of the railway operations, there may be unavoidable delays, which will slow down the freight flow and lead to potential delays in investment return. The cost and the time of changing the locomotives were also considered. The electrification of railways has considerable potential to reduce emissions from the freight transport sector, helping to achieve climate targets, although the mentioned delays were not assessed.

ZENEZINI and MARCO (2020) analyzed the city logistics system, the policy-making process, and its connections to operational and economic factors. The level of emissions was analyzed considering policies promoting electric vehicles. As CO_2 emissions rise, the financial incentives for green vehicles increase, making them more attractive to absorb transport demand. However, the model does not include technical issues, availability of charging stations, and time responses of policies related to alternative fuel adoption.

Figure 2.7 shows the common variables and relationships that form the feedback loops in the SD models related to alternative fuel adoption. Emissions depend on fuel consumption and efficiency, while alternative vehicle adoption takes into account regulations, fuel costs, refueling and recharging station availability, purchase and maintenance costs, as well as drivers' experiences. On the other hand, transport demand and vehicle load lead to an expected fleet, influencing vehicle sales, while incentives to renew the fleet are another option to scrap polluting old vehicles and adopt alternative green technologies.

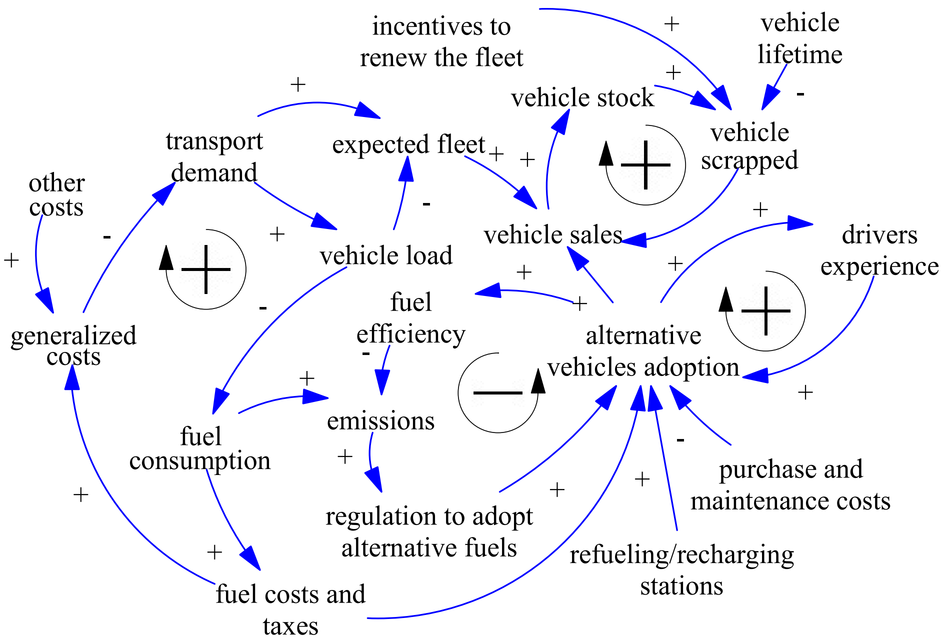

Figure 2.7 – Common dynamic relationships of switching to lower-carbon energy models.
Source: based on BARISA and ROSA (2018a; 2018b); CAGLIANO et al. (2015a; 2015b; 2017); PURWANTO et al. (2011); SETIAWAN et al. (2019); ZENEZINI and MARCO (2020).

Most studies did not present the model equations in the quantitative phase of the SD models, while one showed them entirely, see CAGLIANO et al. (2017), and three (BARISA and ROSA, 2018b; SHAFIEI et al., 2014; ZENEZINI and MARCO, 2020) presented only the main equations. Integration techniques or time steps used were not disclosed. Any delay was discussed or represented in the models, although implementing regulations to adopt alternative fuels, incentives to renew the fleet, or drivers' experience consolidation may not occur instantaneously. In general, there is a lack of discussion about the time responses related to policy enforcement and the willingness of companies to adopt innovations regarding alternative fuels and efficient vehicles. Thus, there is a research opportunity to deepen knowledge associated with the intrinsic dynamics of changing technological paradigms of this decarbonization strategy.

2.4 Final remarks of the chapter

In this chapter, the application of system dynamics models to the policy challenge of decarbonization of freight transport was reviewed. Particular focus was placed on the model's structure, key variables, and dynamic factors, such as delay equations, time-related variables, sequences of stock and flows, and assumptions made to build feedback loops.

The first conclusion of this literature review is related to the limited boundaries of the models to represent the system. Overall, system dynamics models were found for different individual decarbonization strategies, with varying levels of detail. However, any model addressed the five decarbonization strategies for analysis if, how, and when a given level of emissions reduction could be achieved. As described in Section 2.1, freight transport has a systemic nature, whereby changes in one element affect other ones of this system over time. A partial or disconnected view hinders a final assessment of the most effective actions. We see this coordination of different policy measures as a fundamental challenge for the decarbonization of the freight transport system in the coming years. Methods need to be developed to study the interaction of different policy measures.

The second conclusion taken from the literature review analysis is the lack of transparency concerning the empirical modeling of the temporal dimension. Although most authors provide time ranges in their simulation results (see Table 2.1), they are not clear about the background of pathways or the delay assumptions for each decision to achieve the results in those defined terms. Occasional explanations of dynamics related to vehicle utilization and mode shift decisions have been found. Some studies also included delays in governmental policies, market shares, and their impacts on the construction of fueling stations. These are some rare examples of dynamics as a factor in decarbonization pathways. However, we argue that time lags should be considered in an empirically rigorous way for freight transport decarbonization models to predict dynamics well. The dynamic component of the reviewed system dynamics models is often not clear, which is observable through the absence of model equations, system dynamics diagrams, and even model descriptions and assumptions. This is a major problem, not just for the research community, but mostly because time is crucial for assessing whether simulated policy measures effectively achieve decarbonization targets in the short, medium, and long term. For this reason, the SD community should focus on describing the time component of their models, either through actual data or assumptions, to deepen discussions regarding the problem.

Many barriers exist in the testing and validation phases since it is impossible to obtain all necessary data without significant research efforts. Another possible difficulty could be quantifying the factors or relationships between agents, such as lobby practice, regulatory pressure, or market acceptance of new technologies. Therefore, solid assumptions in dynamic models will be unavoidable for some time, but ignoring a causal link or the associated time delay can be worse than making a good guess. Therefore, further research should consider an integrated model with all possible strategies and agents related to freight transport decarbonization and their time-lag decisions to build a more realistic model. A significant opportunity lies in enriching system dynamics models with studies of specific subsystems or decisions, such as the internalization of emissions costs and adopting new technologies and alternative fuels. Such studies can also be executed with time series models or discrete simulation models, independently of the larger system models discussed in this chapter. Based on such empirically validated models, the task of integration into large system dynamics models could be undertaken in future research.

The rebound effect of transport efficiency on logistics costs and product prices and, consequently, on freight demand, should be further analyzed. The time lags could be better investigated for the mode choice process, such as companies' decisions and adaptation time, and the time taken for public and private investments in logistics infrastructure to support the mode shift. It would be interesting to note how companies of different levels react to policies, such as the internalization of external costs, marketing strategies, and the green image of companies and how it impacts the use of their fleets over time. Moreover, analyzing organizational adoption behavior could expose the dynamics and time responses of market diffusion of alternative technologies, considering the competition between different technologies and how it would impact their adoption over time. Table 2.8 summarizes suggestions for deepening the study of the dynamics of each decarbonization strategy.

The current search is subject to improvements, as there may be studies not included here, either because they are in other databases or because they do not contain the keywords used in our search. Even so, our findings are relevant for the scientific community due to the increasing use of system dynamics in the analysis of freight transport decarbonization strategies. Besides highlighting the gaps in the literature, we contribute to future research, since the results assist researchers with their structured discussion about the main decarbonization strategies.

Table 2.8 – Suggestions for future research in each decarbonization strategy.

Decarbonization Strategies	**Suggestions**
Reducing freight transport demand	The dynamic of the market response to product prices or logistic costs should be further analyzed, as well as other policies, such as logistics collaborations, partnerships, and vertical integration, and their effects on freight transport demand.
Shifting freight to low-carbon intensity modes	Warehousing and transshipment costs should be considered, as well as time lags regarding the mode choice process, the network construction time, and companies' adaptation. A cost-benefit analysis could assess secondary benefits, such as road conservation and safety. Further studies could address the gaming processes of multiple stakeholders' competition.
Improving vehicle utilization	The reaction of different companies' levels to the internalization of external costs and other policies and how it impacts the use of their fleets and other asset capacities should be further investigated. Inventory costs and management should be taken into account, as they affect the dynamics of logistics operations. Marketing strategies and the green image of companies could be further analyzed.
Increasing energy efficiency	Analyzing organizational adoption behavior in more detail could expose the dynamics and time responses of market diffusion of alternative technologies.
Promoting alternative energy sources	The lifespan of batteries, fuel cells, and installation and operating costs of refueling and recharging infrastructure could be added to the analysis of the dynamics adoption of alternative vehicles. Models should also consider the dynamics of competition between different technologies and their adoption over time.

The next chapter will present a conceptual model composed of causal loop diagrams, which was drawn based on the literature review, integrating the five decarbonization strategies from a system-wide perspective. This qualitative model contributes to the literature, bringing to light the need for coordination between decisions within the system so that their effects are not minimized or defeated.

3 Dynamics of freight transport decarbonization: a conceptual model

This chapter describes a conceptual model for the freight transport decarbonization system through causal loop diagrams. Published in the Journal of Simulation (GHISOLFI et al., 2022b), we chose to keep the original structure, form, and text as close as possible to the published paper, which justifies a new literature review section, although it is grounded in the literature review presented in Chapter 2. It details the dynamics of the system bringing a broad view with five decarbonization measures, the feedback loops between their components, and the dynamic levers that have the potential to change the system according to the policy instruments applied. Through this conceptual modeling effort, we can identify the rebound effects of policies over the whole system, which could defeat the desired decarbonization results. The proposed qualitative model starts filling one of the gaps found in the literature review carried out by GHISOLFI et al. (2022a), presented in Chapter 2, regarding a model with a system-wide perspective, capable of representing the dynamics between decision-making in different areas of the system.

3.1 Introduction

Climate change is a worldwide concern and the global pressure to decrease greenhouse gas (GHG) emissions is strengthening to reduce negative environmental impacts. According to the Paris Agreement, all parties should put forward a long-term strategy setting out the actions that they will take across the whole economy to contribute to the global goal of limiting the average temperature increase (UNITED NATIONS, 2015). This means that global emissions should decrease significantly by mid-century, mostly led by developed countries (EUROPEAN CLIMATE FOUNDATION, 2018). In this context, a rising number of countries are targeting net-zero emissions by 2050, which will demand a set of ambitious actions over the next years. Decarbonization strategies may have quite specific and narrow time windows to take effect, turning this system into a dynamically complex one. Bringing about a 40% reduction in emissions by 2030, for example, requires that passenger electric cars worldwide increase from 2.5% in 2019 to more than 50% in 2030 according to the World Energy Outlook 2020

(INTERNATIONAL ENERGY AGENCY – IEA, 2020). While many sectors show decreasing emissions of GHG and passenger transport is moving towards electrification and less CO_2-intensive fuel alternatives, freight transport remains heavily dependent on fossil fuels (FRIDELL et al., 2019). The transport sector accounted for 7.219 Mt CO_2 of global emissions in 2020, from which freight transport was responsible for about 37% (only heavy trucks accounted for 24%) (IEA, 2021), which is expected to increase due to e-commerce and home delivery. GUÉRIN et al. (2014) stated that freight transport is one of the most difficult economic activities to decarbonize, especially because the demand for freight movement is expected to increase, and it will be even harder to reduce its huge dependence on fossil fuels over this period.

Transition pathways to low-carbon freight transport systems combine different measures. MCKINNON (2018) proposed five broad strategies to decarbonize freight transportation: (1) reducing the demand for freight; (2) shifting freight to low carbon-intensity modes; (3) optimizing vehicle loading; (4) increasing the energy efficiency of freight vehicles; (5) reducing the carbon content of energy used. This is only possible with top-down policies since the freight transport sector represents a market-driven social, technical, and economic system, which depends on many different private and public stakeholders for its change. These stakeholders may strongly differ in their interests, preferences, decisions, and rules of behavior, which influences the impact of policy options in different contexts (MEASE et al., 2018). Policies that intervene in the system may create unanticipated side effects, leading not only to policy resistance, but also to the tendency for interventions to be delayed, diluted, or defeated (MEADOWS, 1982), impacting the evolution of the system. Thus, besides the mechanisms to decarbonize freight transportation, we should also consider the internal dynamics that lead this process, and the time they take to be effective in different scenarios. By viewing the dynamics of the freight transport system from the context of decarbonization, we can analyze how strategies impact each other through dynamic feedback loops and how this could affect the overall speed of change of emissions reduction. Some strategies can have counter-productive rebound effects and reinforce the use of a polluting mode of transport. For example, increasing truck efficiency leads to road transport costs reduction and increases in its use, in addition to reducing emissions. Therefore, a systemic view allows us to analyze the impact of desirable or concurrent effects. It allows policymakers to understand the critical dynamic levers inside the system and to make them aware that their decisions not only impact the final result but also the time that passes until the system is decarbonized.

Given the problem sketched above, the research question that guides this research is: how can we conceptually model the complexity and dynamics of the freight transport system's decarbonization? In addition to explicitly modeling the mechanisms, we also aim to highlight the dynamic processes of the five decarbonization strategies described by MCKINNON (2018).

We take a systems approach to understand the complexity of this real-world phenomenon, as advocated by Systems Theory and Systems Thinking (KEFALAS, 2011; VON BERTALANFFY, 1972). The application of Systems Thinking is especially useful when a collaborative approach among leaders and individuals must be fostered (LASZLO, 2012). In general, many static-comparative models have already received good acceptance in transport research over the last years, for travel demand modeling and behavioral analysis. However, in our context, the focus is needed on the dynamic environment and strong interdependencies among decisions made at different points in time. In a Systems Thinking context, System Dynamics (SD) modeling stands out due to its adequacy for investigating the impact of policies and strategies over continuous time taking into account the dynamic complexity of feedback-structured systems (ABBAS and BELL, 1994; MAALLA and KUNSCH, 2008; SHEPHERD, 2014).

Our qualitative model is a causal loop diagram that integrates five strategies involved in the decarbonization of the freight transport sector. It depicts the importance of cause-and-effect relationships for researchers and practitioners. The first innovation of our model is that it provides an overview of the freight transport decarbonization system. Divided into connected subsystems, this approach provides the qualitative dynamic behavior of the whole system toward emissions mitigation. This integrated view of the system allows for better coordination of decarbonization strategies, highlighting the need for collaboration between different stakeholders to manage side effects that could reduce the impacts of decarbonization policies. Moreover, the model points out dynamic levers of the system related to the decarbonization objective. These dynamic levers are the main areas of action for policymakers to change the system. In summary, this qualitative analysis contributes to the literature by providing insight into the system of freight transport decarbonization. As a general qualitative model, it can be applied to any geography, since the assumptions taken to construct this model are not specific to a region. It can act as a basis to develop quantitative and empirical SD models of freight transport decarbonization.

The chapter, from this point onward, is structured as follows. Section 3.2 provides a literature review of system dynamics models approaching strategies for freight transport decarbonization. Following, Section 3.3 explains the method used and how the different concepts in this approach help to answer the research question. Then, Section 3.4 presents the causal loop diagrams that describe the system's dynamics. The main feedback loops integrating the dynamics of the proposed model are presented and discussed in Section 3.5. Finally, Section 3.6 presents the final remarks of the chapter and provides suggestions for further research.

3.2 System dynamics modeling and freight transport decarbonization: the state of the art

The SD methodology was developed by Jay W. FORRESTER (1961), as a basis of explanation to illustrate the effects of decisions in complex, dynamic systems, in which the time functions are emphasized. The specific feature of SD is its non-linear feedback structures. For this reason, the interdependencies between system submodules should be identified and illustrated in an iterative modeling procedure (THALLER et al. 2016a).

ABBAS and BELL (1994) discussed and evaluated the strengths and weaknesses of SD concerning its suitability and appropriateness for transportation systems modeling. The authors stated that as transportation problems require integrating forms of knowledge as well as comprise long-term/short-term trade-offs, the SD modeling is well suited for addressing transport problems, especially the strategic studies that are concerned with policy analysis and decision-making. SHEPHERD (2014) presented a review of SD studies categorizing them by area of application in the field of transportation. After an analysis, he provided a summary of insights and recommendations for the future application of the SD approach in this field. At that time, he indicated the lack of research in freight transport and decarbonization using this modeling approach. After that, some SD models addressed specific strategies of freight decarbonization or covered a very particular component of the system to reduce emissions as reviewed by GHISOLFI et al. (2022a) and presented in Chapter 2. Table 3.1 summarizes the specific decarbonization strategies and policies considered in the SD models reviewed by the authors.

Table 3.1 – SD models for freight transport decarbonization, strategies, and policies applied.

Decarbonization strategy	Authors	Policies applied
Reducing freight transport demand	ERDMANN et al. (2004) and HILTY et al. (2006)	Investment in new technologies
	FREEMAN et al. (2015)	Investment in technological efficiency
	KUNZE et al. (2016)	Application of higher transport taxes
	THALLER et al. (2016; 2017)	Not considered
	AGHA et al. (2019)	Increase in fuel prices
	HIDAYATNO et al. (2019)	Carbon tax internalization
	ZHANG et al. (2019)	Not considered
	KAR and DATTA (2020)	Product prices and logistic costs variation
Shifting freight to low carbon-intensity modes	SCHADE and SCHADE (2005)	Higher transport prices (taxes); investment in alternative modes
	HAN and HAYASHI (2008)	Extension of the railway and waterway network and imposition of fuel taxes
	BRITO JUNIOR et al. (2011)	Investment in infrastructure capacities and governmental pressure to reduce CO_2 emissions
	LEWIS et al. (2014; 2015)	Investment in rail infrastructure
	YORK et al. (2017)	Increasing investments in the rail network
	AZLAN et al. (2019)	Promoting alternative modes, such as railway
	CHOI et al. (2019)	Increasing road cost (taxation)
	DONG et al. (2019)	Investment in railway infrastructure
	LIU et al. (2017; 2019; 2021)	Legal truck weight regulation and investment in railway infrastructure
	HU et al. (2020)	Different levels of infrastructure investment policy, network scale, and market competitiveness through price adjustments
	WANG et al. (2021)	Increase the use of alternative modes
	HUANG et al. (2021)	Increasing carbon taxes and investments in the railway network
Improving vehicle utilization	DOLL et al. (2010)	Internalization of transport external costs; allowance of heavier trucks
	ASCHAUER (2013) and ASCHAUER et al. (2015)	Internalization of transport external costs, leading to more pressure to consolidate freight
	OUMER et al. (2015)	Shipment consolidation
	LIU and MU (2015)	Alternative truck weight regulation policies
	SIM (2017)	Not considered
	MELKONYAN et al. (2020)	Investments in digital applications for tracking and tracing and outsourcing the pickup to consumers
	HAMOUDI et al. (2021)	Internalization of CO_2 emissions tax; different levels of truck capacity utilization
Increasing energy efficiency	KRAIL and KÜHN (2012)	Taxes on different technologies and emissions levels
	SEITZ (2014)	Investments in refueling infrastructure and R&D technologies
	SEITZ and TERZIDIS (2014)	Investment in refueling stations and alternative powertrains
	GENG et al. (2017)	Speed reduction, use of shore electricity, engine improvement, and exhaust after-treatment technologies
Promoting new energy sources	FIORELLO et al. (2010)	Incentives for fleet renewal, and increases in fossil fuel prices
	PURWANTO et al. (2011)	New emission standards, penetration of alternative technologies, increase in fuel efficiency, and fleet renewal; fuel quality; incentives for low-emission cars
	SHAFIEI et al. (2014)	Oil price variations, alternative fuel availability, and carbon taxes

Decarbonization strategy	Authors	Policies applied
	CAGLIANO et al. (2015a; 2015b; 2017)	Subsidies for alternative technologies and investment in refueling/recharging infrastructure
	MENEZES et al. (2017)	Improving fuel efficiency and promoting the use of biofuels
	HADDAD et al. (2019)	Not considered
	BARISA and ROSA (2018a; 2018b)	Fossil fuel taxes, subsidies for alternative fuels, investment in refueling/recharging infrastructure, and mandatory use of biofuels
	SETIAWAN et al. (2019)	Efficiency improvements, and adoption of electric vehicles
	ROZENTALE et al. (2020)	Investment in new energy sources
	ZENEZINI and MARCO (2020)	Economic incentives for electric vehicles

Source: Based on GHISOLFI et al. (2022a).

The review of GHISOLFI et al. (2022a) concludes that previous SD models of freight transport systems were too narrow in their representation to study decarbonization strategies, especially at a country level. Although the SD literature does address individual decarbonization measures, there is no model which takes a system-wide perspective to assess by when a given level of decarbonization could be achieved for the system as a whole, with all measures considered together. This is an important gap since a narrow view of unconnected subsystems prevents the identification of the most effective actions and prevents awareness of the dynamic interactions between policy measures during the next decades. Another key concern is the current lack of transparency regarding the mechanisms and temporal dimension of empirical models, including the delay assumptions in key behavioral mechanisms. As the time for decarbonization measures to take effect is limited, this is an important problem for policymakers.

The current chapter addresses the research gap reported by GHISOLFI et al. (2022a), regarding the lack of a comprehensive model in which several strategies interact and are considered simultaneously. To this end, we model the interdependencies between freight decarbonization strategies as well as the contribution of different policies to the total emissions from the freight transport sector, including any rebound effects across subsystems.

3.3 Qualitative analysis approach

The key tool of analysis is the causal loop diagram, which is useful for representing mental models including the feedback structure that determines the dynamic levers of the system (STERMAN, 2000). A causal loop diagram consists of a set of nodes and edges, which illustrates how different variables in a system are interrelated. Nodes represent the variables and edges are the links that represent a cause-and-effect relationship between two given variables. The links have polarities that represent a change either in the same or in the opposite direction. If two variables X and Y are connected by a link (cause-effect-relationship) then the polarity indicated by “+” means that variable Y is increasing when X is increasing and decreasing when X is decreasing. On the other side, the polarity indicated by “-” means that variable Y is decreasing when X is increasing and increasing when X is decreasing.

According to YEARWORTH (2014), the key dynamic concepts that emerge from such diagrams and help to clarify a system’s complex behavior are closed causal loops, identified as either reinforcing (labeled “R” or “+”) or balancing (labeled “B” or “-”). A reinforcing loop indicates that a change in one direction is strengthened by increased change, whereas a balancing loop indicates that a change in one direction can be reversed with a change in the opposite direction. Thus, the reinforcing behavior among the different variables entails exponential growth in the system, while the balancing feedback leads to a goal-seeking or control behavior of the system. There are always delays in the feedback within a closed causal loop, which can range from small to large time intervals. The delay is also considered a key dynamic concept as it can make goal-seeking difficult to achieve. If a delay is added to the system, “the main effect is to introduce oscillation in the system which could be: i) damped and eventually lead to convergence on the desired state; or ii) un-damped and lead to a divergence in which the amplitude of the oscillation grows” (YEARWORTH, 2020, p. 9).

Together, these key dynamic concepts point towards dynamic levers in the system that can be used to study its change and to identify promising policy measures. According to SENGE (1990), solutions focused on dynamic levers can lead to significant improvements, i.e., the best results do not necessarily come from large-scale interventions but can also come from small and well-focused actions (ROXAS et al., 2019). Dynamic levers can be understood as core symptoms, critical variables, points of intervention, tipping points, or simply areas where interventions are deemed most effective, where “a small shift in one thing can produce a big change in everything” (MEADOWS, 1991, p. 1). MEADOWS (1999, as cited in ROXAS et al., 2019, p. 615) proposed 12 leverage points in a system, which were further categorized into three: “(1) physical elements (i.e., indicators, structures and, delays) with the weakest leverage, (2) information and controls (i.e., balancing/reinforcing loops and rules) with medium leverage, and (3) ideas behind the system (i.e., goals) with the strongest leverage". In this sense, dynamic levers can be identified as variables that: (1) are a common cause of multiple effects that can accelerate or decelerate the operation of a system; (2) can be influenced by an intervener, leading the system to major changes; (3) are the root cause characterized by being independent, generating significant and irreversible changes that occur when thresholds have been reached (ROXAS et al., 2019).

So, we explore these dynamic levers further, by the identification of the above properties of the system that affect the response time of the freight transport to decarbonization strategies. The next section describes the model, as built up from the current literature. We first introduce the overall model framework and develop the subsequent parts in separate subsections.

3.4 A causal loop diagram for freight decarbonization

In this section, the developed SD model, illustrated by causal loop diagrams, is derived and explained. The model is divided into submodels to support its transparency and traceability. The submodels, represented by colored arrows in Figure 3.1, relate to subsystems that correspond with the five decarbonization strategies: (1) reducing freight transport demand (red arrows), (2) shifting freight to low carbon-intensity modes (green arrows), (3) improving vehicle utilization (blue arrows), (4) increasing energy efficiency of fleets (purple arrows) and (5) promoting new energy sources (orange arrows). The subsystems are interrelated and influence the output indicator, GHG emissions, placed at the bottom of Figure 3.1.

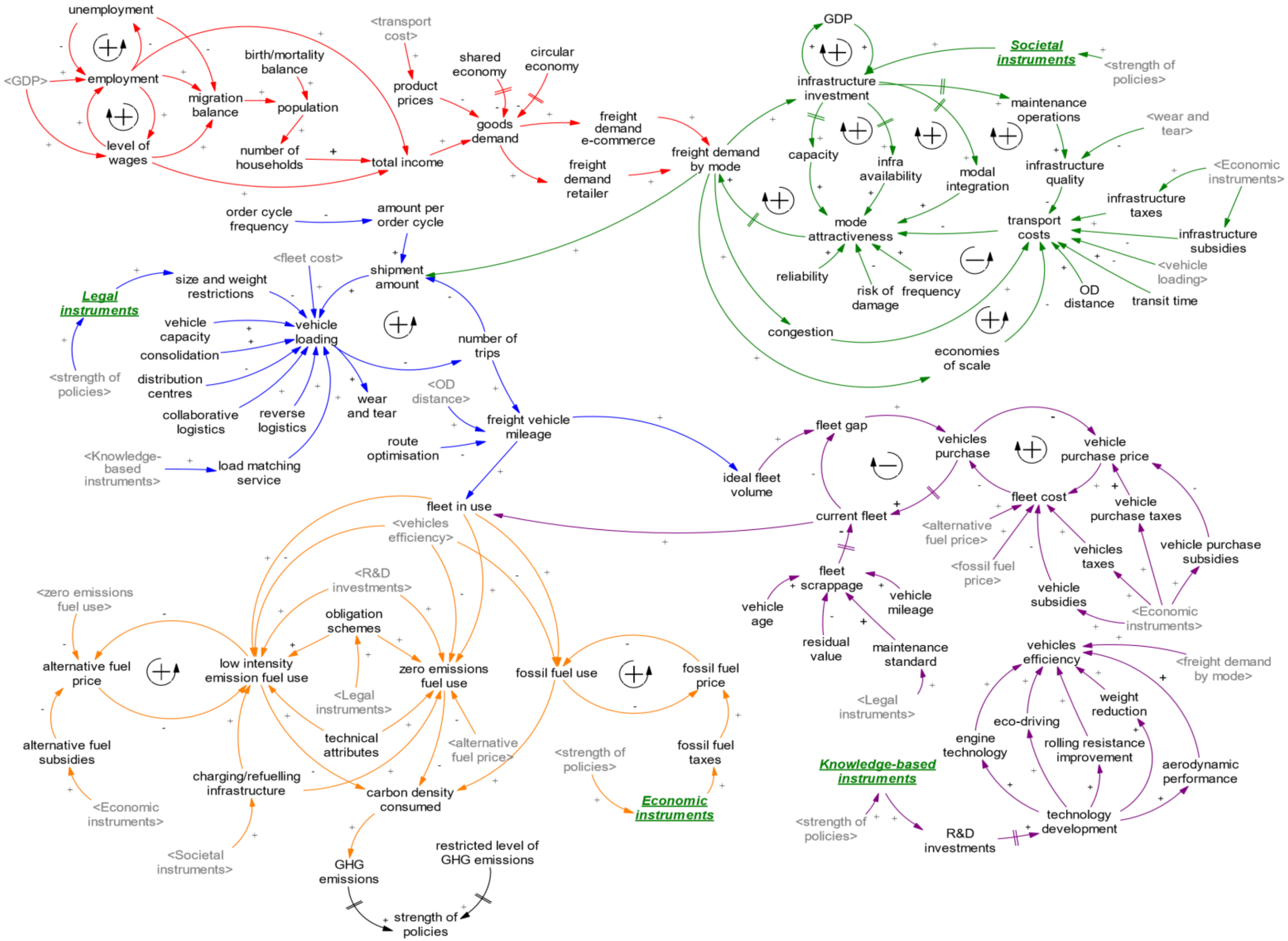

Figure 3.1 – Causal loop diagram for freight transport decarbonization system.

Policies are required to deal with freight external costs such as GHG emissions. The variable “strength of policies” is the sum of all policy instruments in the five submodels taking into account the gap between the real and the admissible level of GHG emissions. Based on STELLING (2014), we considered policies distributed in four categories: economic, legal, knowledge-based, and societal instruments. Economic instruments are all about internalizing external costs by imposing taxes, charges, fees, tax exemptions, subsidies, and others. Legal instruments are mandatory rules to enforce some decarbonization strategies such as truck restrictions (weight, size, and time/zone of circulation), fuel composition, and performance-based standards. Knowledge-based instruments can include information spread to increase customer acceptance of other decarbonization strategies, and Research and Development (R&D) to create new solutions to improve energy efficiency or find alternative energy sources. Finally, societal instruments are related to infrastructure investments to promote the shift from road to less emission-intensive modes, carbon-neutral techniques such as electrical roads, and recharging infrastructure for electrical vehicles. All of these policy instruments are indirectly linked to the “strength of policies” through feedback loops.

Moreover, the “strength of policies” can be more or less rigid according to the established target or admissible level of GHG emissions. It means that policies are dynamic and can be changed, becoming more or less stringent over time as new needs arise, or the level of targeted GHG emissions changes. However, such changes in the “strength of policies” are subject to delays (represented by arrows with hash marks) that result from the decision-making process. Thus, the “strength of policies” is an important dynamic lever to timely achieve the freight decarbonization goal. The different decarbonization strategies and their dynamics are discussed in the next corresponding sections, besides the important variables and connections that build the structure of the model.

3.4.1 Reducing freight transport demand

The first decarbonization strategy is Reducing Freight Transport Demand, which analysis is shown in Figure 3.2. The population grows with a positive birth and mortality balance on the one hand and a positive migration balance on the other. Population development also influences the number of households. Moreover, the economic increase guarantees a positive employment development and the level of wages, which leads to a positive income development of private households and disposable income for consumption. The greater disposable income reinforces the freight demand of the private households in total, which is differentiated in freight demand in location-bound retail branches and freight demand by e-commerce activities via the internet, as these two forms of consumption generate different last-mile logistics services (THALLER et al., 2016b, 2017).

Another factor that influences freight demand is good prices. The prices of the products take into account the transport cost, which in turn, can be influenced by policy instruments like the internalization of emissions costs. If a price increase can be transferred to final consumers by the user-pays principle, the impact will depend on the price elasticity of each product category. According to STELLING (2014), if the taxes correspond to full internalization, the price increase would be substantial.

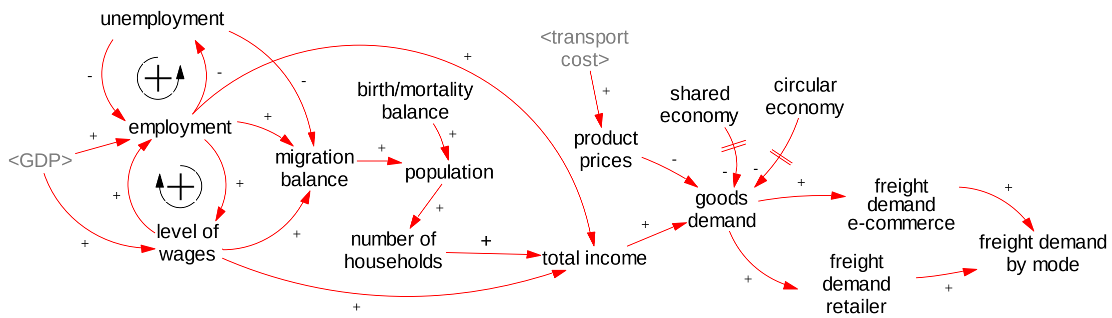

Figure 3.2 – Reducing freight transport demand submodel.

On the other hand, new consumption concepts such as the sharing economy and the circular economy are positive ways of decoupling GDP from freight transport demand. In a sharing economy, consumers prioritize usage over ownership (FRENKEN and SCHOR, 2017), leading to less production, consumption, and, consequently, freight transport demand in the whole supply chain. The circular economy emphasizes reuse, remanufacturing, and repair, before recycling and landfill disposal (KORHONEN et al., 2018). MCKINNON (2018) affirms that such a principle might reduce the level of logistics activities by decreasing the need for the transportation of raw materials or new products. The sharing economy and circular economy are not yet in their maturity stage, however, and may take some time to unfold their impacts.

Another example of the dynamic relationship between consumption patterns and their influence on freight transport demand can be seen in the increase of e-commerce during the COVID-19 outbreak (ARELLANA et al., 2020; BECDACH et al., 2020; LOSKE, 2020), and freight companies had to adapt to the consumption change.

Regarding the dynamic levers of this submodel, delays are present in changes in population and economic development (GDP), as well as other delays in the adoption of new-economy concepts (e.g., circular economy and sharing economy), and the changes in consumer patterns like e-commerce. All these factors dynamically change over time and impact the level of freight transport demand. Although freight demand reduction contributes to emissions mitigation, the predicted trend is an increase in the coming years, more or less linearly with economic growth. Thus, additional measures will be required to deal with freight transport decarbonization, especially within restrictive targets such as net-zero emissions.

3.4.2 Shifting freight to low carbon-intensity modes

The second decarbonization strategy is Shifting Freight to Low Carbon-Intensity Modes since each transport mode contributes to fuel consumption with distinct intensities. Many factors influence the mode choice such as volume of goods demand, cost, flexibility, quality and service frequency, reliability, shipment distance, infrastructure conditions, transit time, cargo damage, and others (HOLGUÍN-VERAS et al., 2021). It is important to consider several factors that influence such a decision to identify dynamic levers. Even when the infrastructure is available, it may not be sufficient to achieve the mode shift goal due to the lack of consensus about operational standards, a failing business-economic rationale, or a conflict of interests between stakeholders (EUROPEAN COMMISSION, 2016). Therefore, considering products that can be carried by different modes, the mode choice depends on many components, as represented in Figure 3.3.

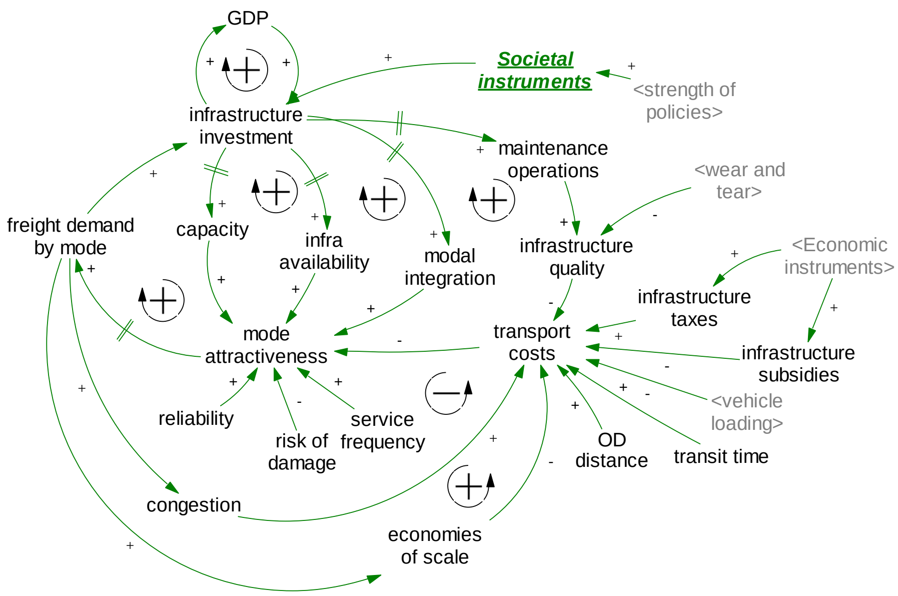

Figure 3.3 – Shifting freight to low carbon-intensity modes submodel.

There are seven feedback loops in this submodel. The first one (at the top of the diagram) shows that infrastructure investments support economic growth and, in turn, an increase in economic development will promote an increase in infrastructure investments. This reinforcement feedback loop may be weak, however, as the transport sector represents a small share of the whole economy (it accounted for about 5% of total Gross Value Added (EUROPEAN COMMISSION, 2021; UNITED STATES DEPARTMENT OF TRANSPORTATION, 2022)). Besides infrastructure availability, capacity, and modal integration, the investments also assure the maintenance operations over time to recuperate its wear and tear, which contributes to its suitability and quality. As demonstrated by the dominance of road transport, these different types of expenditure and mode attractiveness can end up being self-reinforcing (represented by the four positive feedback loops in the middle of the diagram). The next and only balancing feedback loop of this submodel relates freight demand by mode, congestion, transport cost, and mode attractiveness, showing the effect of congestion on transport demand. The last reinforcement feedback loop of this submodel (placed at the bottom of the diagram) relates transport cost, mode attractiveness, and freight demand by mode, showing the effects of economies of scale (the more one mode is used, the more attractive it becomes due to costs savings). These behaviors can be used as part of policies to promote low carbon-intensity modes.

Many delays are identified since the implementation of infrastructure is subject to long and infrequent decision processes, and unforeseen circumstances. The main causes for policy-related delays in this phase are postponements in design information, the lengthy duration for approving the project, and inadequate site management. Furthermore, the delay time is also dependent on the type of project undertaken. Maintenance projects generally experience the most severe delays since they are associated with unpredictable and unforeseen site conditions that often require the relocation of utilities and the redirection of traffic flow (ADAM et al., 2017).

Economic instruments for the internalization of external costs, such as infrastructure taxes or subsidies could also play a role in the mode choice process. ARENCIBIA et al. (2015) confirmed the benefit of policies in favor of charging for infrastructure use, as the actions with the greatest impact on the deviation of traffic to alternative modes are those that affect the cost of transportation. Conflicts of interest between stakeholders can be raised, once road taxation is not differentiated by commodity transported (RIGOT-MÜLLER, 2018), and therefore, such taxes affect manufacturing products with lower values. Additionally, an uneven charging for infrastructure use between modes can benefit one mode over another in terms of operating costs and, consequently, impact their attractiveness and unbalance the use of less polluting modes, as stated by the COMMUNITY OF EUROPEAN RAILWAY AND INFRASTRUCTURE COMPANIES – CER and EUROPEAN RAIL FREIGHT ASSOCIATION – ERFA (2019). Such conflicts are intrinsic to the decision-making process and can delay the mode shift and decarbonization goals.

Dynamic complexity, and consequently the time delays involved in the mode choice process, first depends on infrastructures as well as their accessibility, which can take significant time to be made available either due to bureaucratic concession or bidden issues, project or operational delays. Therefore, the time to implement this decarbonization measure may differ significantly between countries where infrastructure is operational or not. Second, the choice of less-polluting modes is challenging even where the infrastructure is already available, considering the mode attractiveness through cost-utility and the delay with which users shift from one transport mode to another. The actual decision to choose a mode of transport lies with companies, where mode attractiveness determines mode utilization. Delays here can amount to years, if not decades, as companies seldom revisit their choice of mode, if at all. Apart from the low frequency of decision-making, such delays occur due to a lack of readiness to adopt innovations, limited confidence in the future possibilities of new transport modes, difficulties in adapting the logistics organization, or simple inertia. FERRARI (2014) addressed this problem through dynamic cost functions. The application of his model has shown that different evolutions of modal splits in these places occurred because transport costs evolve as a consequence of the overall freight flow increase, the users' attitudes, and the changes in the transport mode technology and organization. The interaction between these causes determines the evolution of the transport costs, and thus, along with the users' delay, the evolution of the modal split (FERRARI, 2014).

HOLGUÍN-VERAS et al. (2021) also argue that the process of freight mode choice is a dynamic system, as its functioning is influenced by the ups and downs of markets as well as by the interactions among the multiple agents involved. The authors estimated discrete choice models to econometrically assess the influence of transit time, freight rate, and generalized cost over the dynamics of mode choice.

In summary, promoting alternative freight modes to trucking will require different efforts such as subsidies, changing companies' preferences and attitudes, enacting faster and more frequent decision-making processes, and understanding needed innovations.

3.4.3 Improving vehicle utilization

The third decarbonization strategy is Improving Vehicle Utilization. Shipping requirements are governed by an operating logistics concept (e.g., Just in Time, Vendor Managed Inventory, and Just in Sequence), which influences the order cycle frequency and amount per order cycle (ASCHAUER, 2013). Figure 3.4 shows the related variables that form this submodel structure.

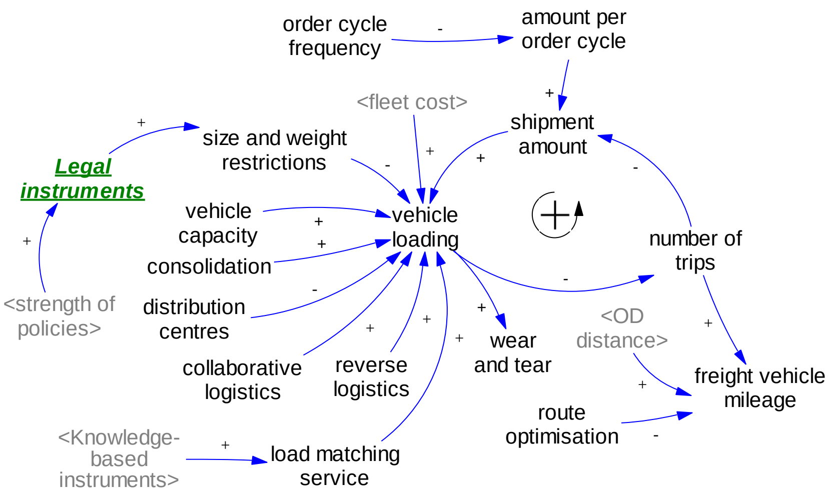

Figure 3.4 – Improving vehicle utilization submodel.

Although heavy vehicles consume more fuel than medium and light vehicles, mainly due to their weights (DEMIR et al., 2011), vehicle loading is inversely related to the number of trips, which means that, as the vehicle load increases, fewer trips are needed to transport a certain amount of load, which reduces costs, fuel consumption, and emissions (LIU et al., 2017). This relationship gives an upward effect on shipment sizes and vehicle loading, forming a reinforcement feedback loop.

Besides shipment sizes and volumes, vehicle loading also depends on vehicle capacity and cargo consolidation, the number of distribution centers, and unavoidable empty runs. MCKINNON and GE (2006) present several reasons and incentives for the decline in empty runs in the United Kingdom, such as outsourcing of haulage operations, multiple destination trips, reverse logistics, and the “digital freight matching” platforms, which usage will increase in the future with the digitalization of the sector. This new type of platform could support a movement for collaboration in fully open and connected networks as envisioned in the so-called Physical Internet System (MONTREUIL, 2011). This “hyperconnected” system could result in GHG reductions of up to 45% (KIM et al., 2021), but it may need a long time (estimated 2040) to materialize due to the many changes needed in standards, procedures, and technology (ALLIANCE FOR LOGISTICS INNOVATION THROUGH COLLABORATION IN EUROPE – ALICE, 2020). The asset utilization can also be improved by local or collaborative procurement by companies (REZAEI et al., 2020), which requires major changes in sourcing practices, or the influence of governments to internalize the external costs of trade. In general, companies will decide more easily to change the sourcing location than to collaborate with other companies, as the latter is not part of their regular decision-making practice. All these factors depend on the frequency with which decisions are taken by the companies regarding the organization of physical distribution and the deployment of their assets.

Size and weight regulations to prevent the overloading of freight vehicles, and to avoid or minimize external costs like accidents and wear and tear, are needed in some countries that heavily rely on roadways and face poor pavement conditions, leading to high logistics and maintenance costs (LIU et al., 2017). On the other hand, the efforts to reduce truck overloading increase transport costs and undermine emissions mitigation due to the increased number of trips.

Beyond the number of trips, freight vehicle mileage is also influenced by the origin and destination distance, and route optimization. An option to reduce freight vehicle mileage is to involve the collaboration of the end consumer in the fulfillment of the last mile. HALLDÓRSSON and WEHNER (2020) claim that energy could be saved in last-mile fulfillment when goods are carried as far as possible collectively down in the supply chain in commercial vehicles with high fill rates, and the end consumer should be responsible for only the last part of the last mile.

Like the previous decarbonization strategies, efficient utilization of the capacity of the vehicles has the potential to reduce emissions, but not to get rid of them altogether. The time to implement this strategy in the future will depend on how companies change their logistic decisions over time.

3.4.4 Increasing energy efficiency

The fourth decarbonization strategy is Increasing Energy Efficiency since it impacts the amount of fuel consumed by conventional internal combustion engine (ICE) vehicles. The fuel consumption will depend on the vehicle technologies in use and the driving practices, as demonstrated in the causal loop diagram of Figure 3.5.

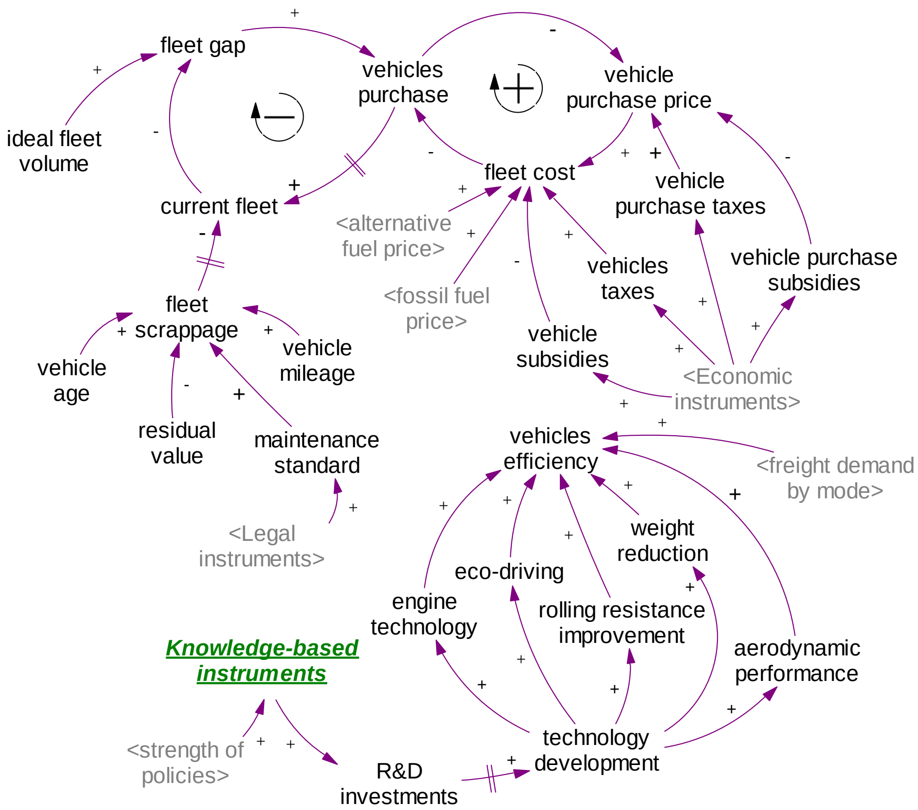

Figure 3.5 – Increasing energy efficiency submodel.

Vehicle technologies that offer potential energy savings are related to weight reduction, aerodynamic drag reduction, rolling resistance, and friction improvements (FOLKSON, 2014). Some of these can be deployed as retrofit technology on the existing ICE vehicles, which brings an early impact. Powertrain technology includes hybrid engines, battery/plug-in/fuel cell electric vehicles, and biofuel addition (FOLKSON, 2014). The dynamic of their introduction is unlike that of conventional technology, due to the need to develop infrastructure networks for battery recharging/swapping (JUAN et al., 2016), and suitable rechargeable energy storage systems (PEREIRINHA et al., 2018). The gains of efficiency improvement are observed in the reduction of fuel consumption, present in the next submodel.

The fleet renewal process is another way to promote energy efficiency improvement. The current fleet can be renewed with the adoption of more efficient vehicles. The organizational adoption behavior for new products or technologies takes place in the setting of organizational buying processes, which influences adoption behavior and the underlying criteria in a process-orientated way (SEITZ, 2014), including higher specificity of demand, a higher number of persons involved, a stronger tendency towards rationality and a longer purchase decision process (WEBSTER and WIND, 1972). The market share of conventional or alternative powertrain concepts is a function of an organization's familiarity, perceived technological attractiveness, and vehicle availability (SEITZ and TERZIDIS, 2014). The vehicle purchase is defined by the fleet gap, that is, the difference between the current fleet and the ideal fleet to attend to the demand, forming a balancing feedback loop. Vehicle purchases also depend on fleet costs and vehicle purchase prices. Technology solutions to improve vehicle efficiency make them more expensive than ICE vehicles. Significant reductions in purchase prices of new technology solutions will be necessary before they make a relevant contribution to total vehicle sales. This is a vicious circle as costs will not reduce until sales increase, and sales will remain low until costs come down (FOLKSON, 2014), as demonstrated by the reinforcement feedback loop. Subsidies for alternative technologies and taxes for old fleets may be needed to promote the entrance of more efficient vehicles into the market.

The fleet renewal process is also related to the scrappage of old vehicles, which depends on the vehicle's age, mileage, and residual value (HUO and WANG, 2012). While the decision to replace a vehicle with a greener model ultimately rests with the commercial entity that owns or operates the fleet, governments can regulate schemes to encourage the replacement of inefficient vehicles and offer green transport subsidies as dynamic levers to encourage the adoption of the most up-to-date technologies. Another important factor impacting fuel consumption is the vehicle's state of repair since poorly maintained vehicles consume more fuel (GREENE and FAÇANHA, 2019). Legal instruments regulating maintenance frequencies and vehicle taxes differentiated according to environmental and safety performance could also be taken as dynamic levers to increase the standard of the vehicles, induce fleet renewal, and hence decrease emissions (STELLING, 2014).

The urgent need to promote the entry of new technology vehicles into the market results from the renewal process that generally takes a long time, considering vehicle economic lifetimes from six to more than 20 years (EUROPEAN AUTOMOBILE MANUFACTURERS ASSOCIATION – ACEA, 2021). Progress towards renewing fleets has been uneven across countries, with developed nations adopting the cleanest

Euro VI equivalent standards, while most developing countries still operate pre-Euro class vehicles (MILLER and JIN, 2018). Developing countries face challenges in the fleet electrification process such as the development of battery charging networks, grid capacity, and affordability of vehicles. The import market of used ICE trucks from Europe and North America at cheaper prices tends to discourage developing countries to switch to low-carbon vehicles. Moreover, the longer life of low-carbon trucks tends to delay their export as used vehicles, and the scarcity of raw materials and reliance on recycling will discourage the export of used batteries and fuel cells (MCKINNON, 2020), making the process of decarbonizing freight even more challenging for developing countries.

The delays related to technology development indicate a slow cycle and new alternative technologies will likely take decades to develop. The USA, Japan, and China dominate R&D funding for key climate technologies (UNITED NATIONS FRAMEWORK CONVENTION ON CLIMATE CHANGE, 2017) while developing countries lag in non-renewable innovation. Depending on the availability of technologies across borders, this aspect may impact the global dynamics of the implementation of decarbonization policies.

The dynamic components of this submodel are the current fleet, vehicle purchase, and fleet scrappage. The reinforcing feedback loop between vehicles purchase and their prices shows that new technologies will not get into the market without incentives for users' acceptance and will not even be produced without a promising market outlook for vehicle manufacturers. It may take 5-15 years, in some cases longer (ACEA, 2021), before innovations can penetrate the market, which means that the effects on the climate will take at least this long to materialize. To deal with all presented delays, implementing specific dynamic levers such as policies for fleet renewal are needed.

3.4.5 Promoting new energy sources

The fifth decarbonization strategy is Promoting New Energy Sources and alternative fuels with low carbon density to mitigate emissions. We considered alternative fuels those zero emissions such as electrification and hydrogen, as well as low-intensity emissions fuel, such as biofuels. Figure 3.6 shows the variables considered in this submodel.

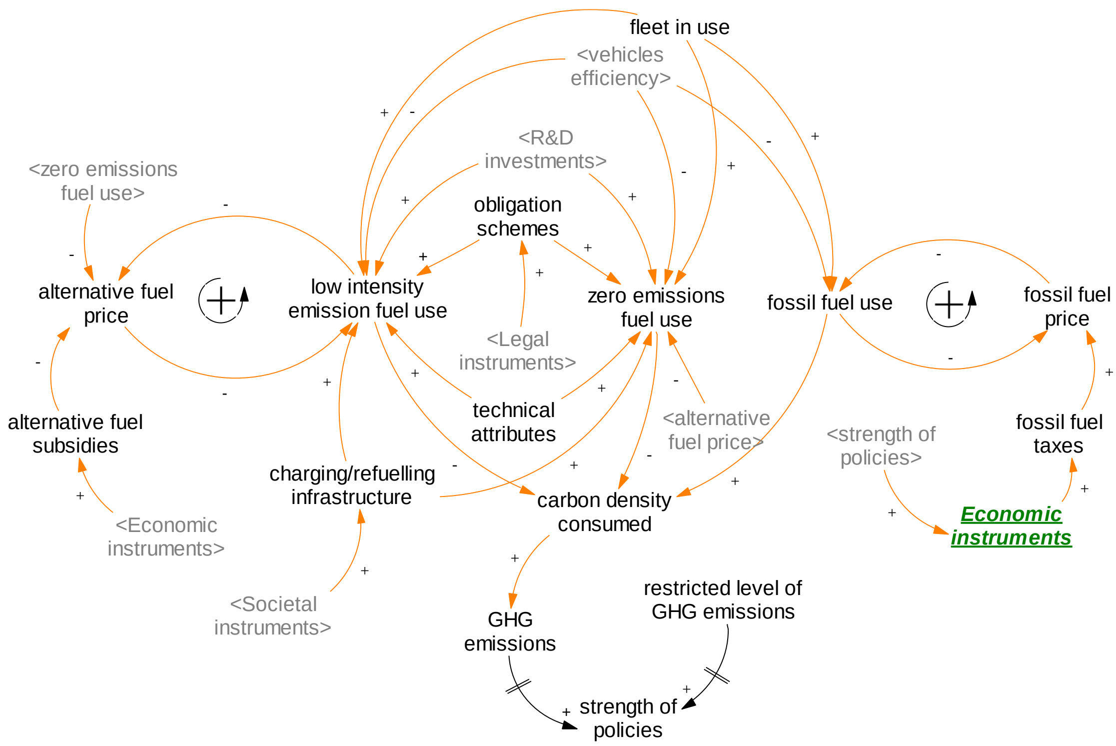

Figure 3.6 – Promoting new energy sources submodel.

The adoption of one type of fuel over another depends on (1) financial attributes (vehicle purchase price, fuel price, and efficiency); (2) technical attributes (driving range, recharging time, performance, brand, diversity, and warranty); (3) infrastructure attributes (charging/refueling infrastructure availability); and (4) policy attributes (reducing purchase price, purchase tax, annual tax, and toll) (LIAO et al., 2017). The two reinforcement feedback loops show that prices of both fossil and alternative fuels have to be considered as they compete and influence the adoption of one over another. Moreover, the gradual availability of charging or refueling service points is a key factor for successful alternative fuel adoption over time.

Fuel price depends on production or import costs, and transport may compete with other sectors, bringing implications for alternative energy supply systems. For example, the rise in oil prices led to a sharp increase in biofuel production. However, some commodities can be used either as food, feed or to make biofuels. Therefore, food versus fuel is the dilemma regarding the risk of diverting farmland or crops for liquid biofuel production to detriment of the food supply on a global scale (DEMIRBAS, 2011). The greater the alternative fuels subsidies and their demand, the greater will be its competitiveness for energy resources in other sectors (MANSSON, 2016), which brings a complex dynamic among the stakeholders involved, affecting the adoption of biofuels over time. A similar thing happens to hydrogen, for which the transport sector seems to be less interesting than the heavy industry market. Even when green hydrogen production costs turn out to be more competitive by 2030, according to the INTERNATIONAL RENEWABLE ENERGY AGENCY – IRENA (2020), there will be competition between these sectors, driving up the price of hydrogen for transport. Such decades-long transition programs should take these dynamics into account and make them transparent for the transport sector.

Fuel taxation for fossil fuels or subsidies for alternative fuels may stimulate the adoption of renewables. Raising diesel prices can be an effective approach when aiming to speed up alternative fuel market diffusion (CAPROS et al., 2016). Legal instruments are also dynamic levers to promote the alternative fuels penetration rate into the market such as the obligation schemes or blending targets, e.g., to include a certain percentage of biodiesel in fuels (STATTMAN et al., 2013). FOLKSON (2014) highlights the compatibility of renewable liquid fuels with current technologies as a benefit. TEIXEIRA et al. (2020) discuss preferences for business-as-usual fuels over more environmentally friendly options. Liquid alternative fuels can be deployed faster than technologies that require heavy investments in technology and infrastructure. However, biofuels will not be enough to meet emission reduction targets and there is an additional need for alternative electrified powertrains with noteworthy emission reduction potentials (PLÖTZ et al., 2019). In other words, accelerating the adoption of low or zero-carbon technologies is essential to achieving deep system decarbonization. Many factors influence their adoption, such as users' preferences, positive experiences of other companies, and payback time (BOER et al., 2013). High costs, limited range, long recharging times, and a lack of adequate fast-charging networks are some of the drawbacks still related to cleaner technologies. A slow entrance into the market of new technologies hinders the option to purchase modern second-hand vehicles, and the barrier of their high costs will remain until this secondary market is available. It is probably for this reason that adoption has only started in countries with generous subsidy schemes. In addition, the climate-mitigating effect of these vehicles will only be effectuated once green energy sources become available at the scale needed. The modeling of these processes in the decades ahead could help to optimize the subsidy policies.

3.5 Discussion

Based on the proposed conceptual dynamic model for freight transport decarbonization, in this section, we discuss the feedback loops between the submodels that integrate the dynamics of the system. An important aspect of the proposed model worthy to highlight is that the submodels of each decarbonization strategy are interconnected, through shadow variables, forming feedback loops that are not directly visualized. This approach is important to show the conflicts and affinities that can exist between the different decarbonization strategies since many efforts are required to decarbonize the freight sector, and interventions can result in side effects not understood when implementing each strategy individually. The feedback loops that integrate the proposed model are presented in Figure 3.7.

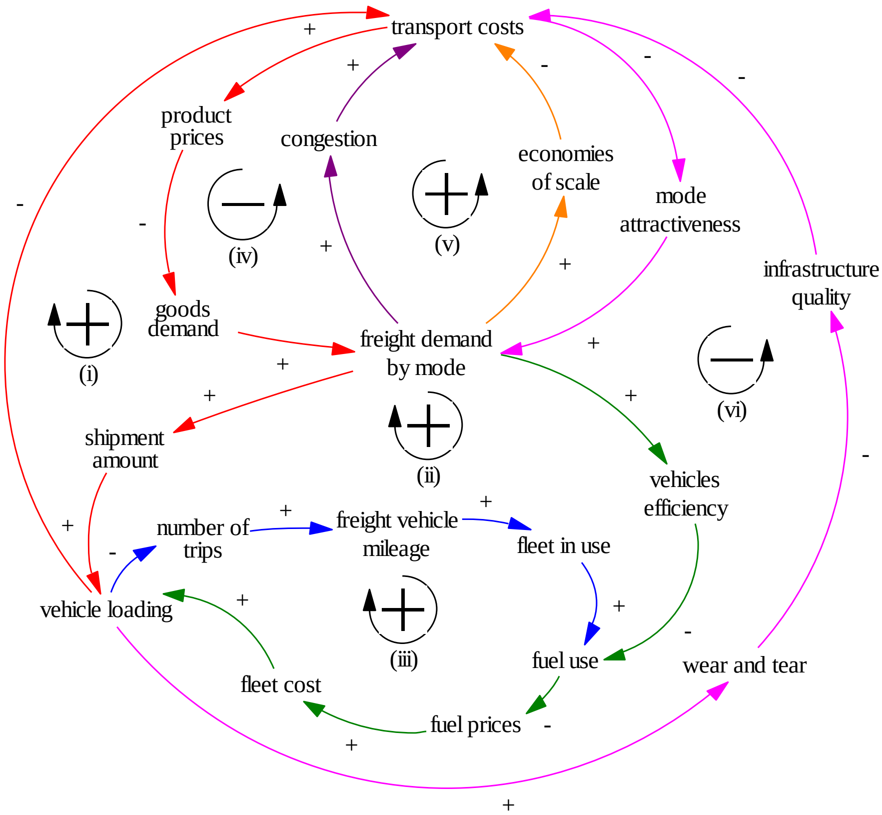

Figure 3.7 – Feedback loops between the submodels of the freight transport decarbonization system.

The first four indirect feedback loops identified between the submodels describe the rebound effect of more efficient freight transport, leading to transport cost reductions, lower products prices, and thereby increased demand, due to the effect of cost elasticity of road transport performance (JONG et al., 2010; FERRARI, 2016), which reinforces efficiency due to economies of scale. Transport efficiency is expressed in terms of better vehicle utilization, freight demand by mode, vehicle efficiency, and fuel prices, dynamically linking the related decarbonization strategies over time.

The first feedback loop shows that the increase in vehicle loading reduces transport costs, influencing product prices, goods demand, freight demand by mode, shipment amount, and vehicle loading in a reinforcing loop:

i. vehicle loading $\longrightarrow^{-}$ transport cost $\longrightarrow^{+}$ product prices $\longrightarrow^{-}$ goods demand $\longrightarrow^{+}$ freight demand by mode $\longrightarrow^{+}$ shipment amount $\longrightarrow^{+}$ vehicle loading (reinforcing loop).

The second feedback loop represents the dynamics of vehicle efficiency gains, reducing fuel use, and influencing fuel price, fleet costs, vehicle loading, transport costs, product price, goods demand, and freight demand by mode, leading to a reinforcement of vehicle efficiency:

ii. vehicles efficiency $\longrightarrow^{-}$ fuel use $\longrightarrow^{-}$ fuel price $\longrightarrow^{+}$ fleet cost $\longrightarrow^{+}$ vehicle loading $\longrightarrow^{-}$ transport cost $\longrightarrow^{+}$ products price $\longrightarrow^{-}$ goods demand $\longrightarrow^{+}$ freight demand by mode $\longrightarrow^{+}$ vehicles efficiency (reinforcing loop).

The third feedback loop indicates that both fossil fuel and alternative fuel prices increase the fleet cost that induces better vehicle utilization, influencing transport costs, products price, goods demand, freight demand by mode, shipment amount, vehicle loading, number of trips, freight vehicle mileage, the fleet in use, and fuel use, leading to a reinforcing loop of fuel prices:

iii. fuel price $\longrightarrow^{+}$ fleet cost $\longrightarrow^{+}$ vehicle loading $\longrightarrow^{-}$ transport cost $\longrightarrow^{+}$ products price $\longrightarrow^{-}$ goods demand $\longrightarrow^{+}$ freight demand by mode $\longrightarrow^{+}$ shipment amount $\longrightarrow^{+}$ vehicle loading $\longrightarrow^{-}$ number of trips $\longrightarrow^{+}$ freight vehicle mileage$\longrightarrow^{+}$ fleet in use $\longrightarrow^{+}$ fuel use $\longrightarrow^{-}$ fuel price (reinforcing loop).

The fourth feedback loop shows that the freight demand by mode also influences congestion, transport cost, product price, goods demand, and freight demand by mode. Especially for roadways, the increase in demand can lead to congestion given the limited capacity of roads, discouraging the use of this transport mode:

iv. freight demand by mode $\longrightarrow^{+}$ congestion $\longrightarrow^{+}$ transport cost $\longrightarrow^{+}$ products price $\longrightarrow^{-}$ goods demand $\longrightarrow^{+}$ freight demand by mode (balancing loop).

The fifth feedback loop relates freight demand by mode, economies of scale, transport costs, product prices, goods demand, and freight demand by mode. This loop is especially important for alternative modes (railways and waterways) as the increase in freight flow and service frequency play an important role in the reinforcement of their use due to economies of scale:

v. freight demand by mode $\longrightarrow^{+}$ economies of scale $\longrightarrow^{-}$ transport cost $\longrightarrow^{+}$ products price $\longrightarrow^{-}$ goods demand $\longrightarrow^{+}$ freight demand by mode (reinforcing loop).

These five feedback loops are particularly important for the first stage of decarbonization, as efficiency improvements are interesting, not only because of their environmental benefits but also because they are economically profitable. As the efforts to reduce CO_2 emissions become more expensive, transport costs will not be reduced anymore (or will even increase). Therefore, dynamic levers should be combined to reduce the rebound effect of efficiency gains on the freight transport demand to mitigate emissions.

The sixth and last feedback loop shows that the vehicle loading is directly related to the wear and tear of the infrastructure used. Then, wear and tear influences infrastructure quality, transport costs, mode attractiveness, freight demand by mode, shipment amount and finally returning the effect to vehicle loading in a balancing feedback loop:

vi. vehicle loading $\longrightarrow^{+}$ wear and tear $\longrightarrow^{-}$ infrastructure quality $\longrightarrow^{-}$ transport costs $\longrightarrow^{-}$ mode attractiveness $\longrightarrow^{+}$ freight demand by mode $\longrightarrow^{+}$ shipment amount $\longrightarrow^{+}$vehicle loading (balancing loop).

Since wear and tear mostly affect the roadway mode, this feedback loop indicates that increasing truck loading undermines pavement conditions and the attractiveness of roadways. The effect of this loop on roadway use will depend on many other factors outside the loop. Moreover, this effect is considered negligible for railways and waterways.

In summarizing, our dynamic causal loop diagram contributes to understanding how complex patterns of freight decarbonization are as an endogenous consequence of the structure of a system ruled by multiple non-linear feedbacks, and allowing for strategy and policy analysis. The broad boundary model captures several of the most important feedbacks governing the behavior between the freight demand patterns, choice of transport modes, utilization of vehicle capacity, fleet efficiency improvement, and alternative fuel diffusion. Although no quantitative results are provided at this stage, this comprehensive view of the freight decarbonization system, provided by the qualitative model, underscores the importance of applying a set of policies rather than isolated actions. For example, it would not be enough just to promote policies to encourage low-carbon technologies, it is also necessary to impose restrictive policies on internal combustion vehicles so that the environmental and economic advantages are reinforced in a combined way. Another example that highlights this aspect is the rebound effect of road transport efficiency increase, which ends up reducing costs and increasing demand. In this sense, it is important to have demand management policies, so that the rebound effect does not eliminate the environmental advantages obtained by increasing efficiency.

3.6 Final remarks of the chapter

In this chapter, a causal loop diagram for studying the dynamics to decarbonize the freight transport system has been developed. The contributions of this model can be summarized as follows:

- The model provided an overview of the freight transport system. This approach shows that the system is not composed of isolated subsystems, but that they interact with each other, providing the dynamic behavior of the whole system;
- The model linked five decarbonization strategies, showing the dynamics and feedback loops between their main components to evidence that these strategies affect each other in a reinforcing or balancing way;
- The model pointed out the dynamic levers as policies to promote or stimulate decarbonization, which should be the focus of policymakers; and
- The model provides an integration of distinct decarbonization strategies subsystems allowing more in-depth studies and filling a gap identified in the literature, which collaborates with the developments in this academic field.

The main dynamic levers identified in the proposed causal loop diagram are directly and indirectly related to policies' implementation and divided into economic, legal, social, and knowledge-based instruments, such as taxes or subsidies, R&D, information, and maturation of new technologies, infrastructure investments for alternative modes or more efficient vehicle and fuel adoption. Besides the decarbonization strategies and specific policies within each strategy, acting as leveraging points, the identified feedback loops are also dynamic levers that show how the whole system is connected. It shows the policymakers the possible indirect side effects of their policies that could defeat the desired results. All of these dynamic levers take part in the system's change over time, affecting the freight transport demand, the infrastructure used, the fleet technology, and how its use is optimized.

Although full decarbonization might only be achieved with a radical technological change, the presented strategies all contribute toward freight transport decarbonization. Given the magnitude of the emissions reduction required over the next few decades, decarbonization must be approached systematically, exploiting all the opportunities. In this sense, the proposed model contributes to showing the big picture of the system with its feedback loops and dynamic levers which are critical to achieving the desired results.

This qualitative analysis contributes to the literature with insights about the dynamics of the implementation of decarbonization strategies that can delay or speed up the system's change over time due to the behavior of exponential growth or balancing feedback loops (polarities are an important result of our work). In this sense, this work contributes, in a qualitative way, to close the literature gap of a model that integrates the dynamics of different decarbonization strategies, as highlighted in the literature review (GHISOLFI et al., 2022a), presented in Chapter 2. However, we recognize that with the current work it is not possible yet to set priorities for policies, a quantitative model simulating their impacts within the system is required.

For further research, this causal loop diagram should be converted into an empirical quantitative model, and scenarios should be simulated considering uncertainties about technology, policies, lobby practice, regulatory pressure, and market acceptance. As a key factor for new technologies adoption, the market acceptance, as well as the organizational buying process and the behavior analysis, should be further investigated for a more reliable and holistic understanding of the market penetration of alternative powertrain concepts in the market of heavy commercial vehicles.

As a general qualitative model, it can be applied to any geography, since the assumptions taken to construct the model are not specific to a region. However, as the contexts of countries or regions differ, these should be considered in the quantitative approach to show the effect of decarbonization strategies implemented in distinct realities. For example, besides mandatory regulations, some complementary policy instruments, implemented voluntarily, have emerged in some countries to encourage sustainable freight practices, such as the SmartWay program in North America (BYNUM et al., 2018), the China Green Freight Initiative in Asia (LIU et al., 2019), the Lean and Green program in Europe (KALEDINOVA et al., 2015), and the "FRET21" in France (TOURATIER-MULLER and ORTAS, 2021). However, other countries differ from this reality. In India, KUMAR (2021) underlines a lack of coordination between freight logistics organizations and public entities. In Brazil, apart from the use of enforcement legislation, FROIO and BEZERRA (2021) point out the difficulties of involving shippers in sustainable freight projects, while other policies such as increasing the use of biofuels can be more easily explored due to the production facilities in this country. All these context-specificities should be considered.

Based on the conceptual model presented in this chapter, the next chapter proposes a simulation model that numerically investigates the impacts of some freight decarbonization policies, and how their related temporal factors influence the emissions mitigation results.

4 Dynamics of freight transport decarbonization system: a simulation model

This chapter describes a mathematical model for the freight transport decarbonization system through stock-and-flow diagrams of the System Dynamics methodology. Based on the conceptual model proposed by GHISOLFI et al. (2022b) and presented in Chapter 3, we have made some assumptions to simulate four different policies. Using a broad conceptual model as a basis, the present simulation model numerically investigates the temporal dynamics involved in the implementation process of specific freight decarbonization measures, partially contributing to closing this gap in the literature, as pointed out by GHISOLFI et al. (2022a) and presented in Chapter 2. The model offers a perspective on the need to strengthen policies in the coming years and decades if we are to decarbonize freight transport. In addition, the results showed that the sooner the combined measures are implemented, the greater the potential for reducing emissions in the long term, contributing to the achievement of audacious environmental goals for the sector. This chapter was designed (text, format, structure) aiming to submit it to a scientific journal.

4.1 Introduction

Freight transport is the reflection of a dynamic economy. However, this sector also brings emissions, traffic, and congestion among other negative externalities. The INTERNATIONAL TRANSPORT FORUM (ITF, 2015) estimates that international trade-related freight transport accounts for around 30% of all transport-related CO_2 emissions from fuel combustion, and more than 7% of global emissions. According to the INTERNATIONAL ENERGY AGENCY (IEA, 2022), following a net zero emissions target by 2050 requires transport sector emissions to fall by about 20% by 2030. Achieving this drop would depend on a broad set of policies, such as the rapid electrification of road vehicles, operational and technical energy efficiency measures, the commercialization and scale-up of low-carbon fuels, and policies to encourage a modal shift to lower carbon-intensive travel options. However, achieving the desired results requires articulating multiple stakeholders' interests to design and implement actions consistent with long-term decarbonization goals (BATAILLE et al., 2016).

As a dynamics complex system, freight transport has multiple agents making decisions that can impact the whole system through feedback responses. Regardless of the decarbonization strategy adopted, decision-makers must be aware that their policies, decisions, and actions may have second-order effects, leading to the need for a system macro perspective (GHISOLFI et al., 2022b). Besides the impacts of second-order effects, the system's dynamics are also determined by the speed of change, i.e., the time that each decision or action takes to be implemented and take effect. For example, developing alternative fuel vehicles (AFV) is a relevant strategy for freight decarbonization, but knowing when the technologies will be adopted and used on a large scale is critical for crafting more realistic decarbonization targets and addressing the problem more efficiently.

Developing economies emerge as interesting cases to analyze, since the freight demand in these countries is expected to increase on a larger scale (ITF, 2019), while social, economic, and political constraints impose unique conditions for policy design, commonly with fragmented logistics operations, inadequate infrastructure, and a lack of proper policy making (DÍAZ-RAMIREZ et al., 2017). Within the current commitments of the Brazilian Government to international agreements, in terms of emissions reductions, some policy initiatives have been implemented. Yet, "How will these policies contribute to the goal of decarbonization in the long term?", "How long will it take?" and "What are the differences among the policies, in terms of their effectiveness?" are questions that remain unanswered. In this sense, this chapter aims to investigate the impact of policies in the long term for freight transport decarbonization in Brazil.

To do so, we have taken a systems approach that focuses on the dynamics and interdependencies among policies and decisions made at different points in time. System Dynamics (SD) modeling stands out due to its adequacy for investigating the impact of policies and strategies over continuous time taking into account the dynamic complexity of feedback-structured systems (ABBAS and BELL, 1994; MAALLA and KUNSCH, 2008; SHEPHERD, 2014).

The remainder of this chapter is organized as follows. Section 4.2 brings a literature review of different approaches that address the dynamics of the freight transport system, and justifies the choice of the SD methodology for this research. Section 4.3 presents the material and methods with a geographical background of the chosen case study for the model application, the qualitative research conducted through interviews with experts, the quantitative SD modeling, data used, model tests, and sensitivity analysis. Section 4.4 presents the scenarios set and results of the simulations. Section 4.5 brings the discussions while Section 4.6 presents the final remarks of the chapter and indicates future research directions.

4.2 Literature Review

Dynamics are generally defined as the forces or properties which stimulate growth, development, or change within a system or process. It can be understood as the multiple, mutual, and continuous interactions of all the levels of the developing system, leading to a nested process that can unfold over many time scales (THELEN and SMITH, 1998).

The need to understand the dynamics of freight systems has grown in importance since policies need to be adapted to time-definite objectives like decarbonization. Therefore, we need to understand who takes decisions about which aspects of logistics and when (i.e., in what sequence and with which frequency) (TAVASSZY, 2020). In this sense, RIOPEL et al. (2005) presented 48 interrelated logistics decisions at the strategic planning, network, and operational levels that, directly or indirectly, drive freight transport. Specifically in the transportation level of logistics, eight decisions can be under concern (transportation modes, types of carriers, carriers, degree of consolidation, transportation fleet mix, assignment of customers to vehicles, vehicle routing and scheduling, and vehicle load plans). Although the framework proposed by RIOPEL et al. (2005) emphasizes the multiple links and the complexity of the resulting logistics decision (i.e., for each decision, the authors show the preceding logistics decisions, as well as additional information required to make the decision), the related temporal effects and dynamics in a comprehensive study are still lacking (TAVASSZY, 2020).

To address and model the dynamics of a system, we can take different approaches such as time series models, agent-based modeling (ABM), and system dynamics (SD). Time series is defined as the sequence of observations of a given variable over time. In empirical economic analysis, for example, it is needed to study the relevant links among the observations, helping decision-making and forecasting future values (GOURIEROUX and MONFORT, 1997). ABM, in turn, is a stochastic bottom-up modeling approach, based on a set of agents and interaction rules in each environment. Agents are discrete individuals with given characteristics and behavioral rules. ABM models can express and characterize heterogeneity, including spatial interactions within and between agents (MAIDSTONE, 2012). Thus, ABM is the preferred method when complex events exist due to heterogeneous actors. On the other hand, SD is a deterministic top-down modeling approach that describes systems from a wide perspective, focusing on dynamic complexity which arises from the system's structure, feedback, and time lags (SHEPHERD and EMBERGER, 2010). The SD approach largely depends on assumptions about the homogeneity of modeling entities (TEOSE et al., 2011), and it is used for policy analysis and design in systems with information feedback, interdependence, and mutual interaction (LEWE et al., 2014). Thus, SD provides a structured framework, through which large-scale systems can be modeled, analyzed, and tested (ABBAS and BELL, 1994; SHEPHERD, 2014). This method evidences the relationship between interrelated variables (cause and effect) and demonstrates the impact of variables that change in different timeframes.

Regarding time-series and ABM models to represent the dynamics of freight transport systems, different aspects were addressed by the models in the literature. HOLGUÍN-VERAS (2002) modeled the commercial vehicle choice process using a discrete-continuous choice model. Later, HOLGUÍN-VERAS et al. (2021) also used discrete-continuous choice models to represent the choice of rail or truck for different commodity types, and different combinations of independent variables and weighting schemes.

DI FEBBRARO et al. (2011) proposed a dynamic model for a freight delivery plan which is applied until an external event occurs and a new freight delivery plan is needed. To improve the financial model of an urban distribution center, VAN DUIN et al. (2012) investigated a dynamic fee for its usage. The model provided insights into the dynamic behavioral interaction between stakeholders in city logistics.

FERRARI (2014) presented a dynamic modal split in a multimodal freight transport system, which supposes that the evolution over time of transport demand is accompanied by a corresponding evolution of the transport mode characteristics. The model is based on the paradigm of random utility but introduces the dynamic cost functions and takes into account the users' delays to switch from one transport mode to another. ANAND et al. (2014) developed an ABM for analyzing the urban freight delivery processes, implementing a last-minute order scenario, which reduces the number of trucks and the total distance traveled in the urban system.

SCHRÖDER and LIEDTKE (2017) proposed a multi-agent simulation that consists of disaggregate traffic. Congestion effects and resulting delayed arrival times are fed back into the demand models where agents can evaluate their plans with individual utility/cost functions quantifying travel times and distances, activity durations as well as delayed arrival times. Based on the agent's experiences in previous iterations, it can choose a different route, another transport mode, departure times, or vehicle (fleet size, vehicle types, and activity sequences).

LEPITZKI and AXSEN (2018) developed a dynamic vehicle choice model that incorporates technology, costs, changes in travel demand, and endogenous fuel supply decisions. In each time step, a portion of the existing vehicle stock is retired, and demand for new vehicle technologies is assessed. The model simulates how heterogeneous consumers purchase different vehicle technologies based on capital, energy, maintenance, and intangible costs.

REIS (2018) proposed an ABM of a freight transport market in which agents interact through simulated auctions of transport contracts in which a dynamic price calculation mechanism has been devised to simulate agents' specific pricing strategies. A discrete trust function was proposed to simulate the level of trust between a shipper agent and every freight forwarder agent. GATTA et al. (2020) developed an ABM to simulate the optimal last-mile delivery process from the supermarkets to final consumers to evaluate the potential of e-grocery adoption.

Regarding SD models, ABBAS and BELL (1994) discussed and evaluated their strengths and weaknesses in terms of suitability for modeling transport systems. As transport problems require ways of integrating knowledge as well as including long/short-term trade-offs, SD modeling is suitable for addressing many transport problems, especially strategic studies that are concerned with policy, analysis, and decision making as reviewed by SHEPHERD (2014).

Concerning the freight emissions problem, in the last years, some SD models addressed specific strategies or covered a very particular component of the system, as pointed out by GHISOLFI et al. (2022a) and presented in Chapter 2. After a systematic review of SD models covering decisions about transport demand management (FREEMAN et al., 2015;

KUNZE et al., 2016; AGHA et al., 2019; HIDAYATNO et al., 2019; KAR and DATTA, 2020), mode choice (YORK et al., 2017; CHOI et al., 2019; WANG et al., 2020), assets capacity utilization (ASCHAUER et al., 2015; SIM, 2017; MELKONYAN et al., 2020), use of energy-efficient technologies (KRAIL and KÜHN, 2012; SEITZ, 2014; SEITZ and TERZIDIS, 2014) and alternative fuels (SHAFIEI et al., 2014; CAGLIANO et al., 2017; MENEZES et al., 2017; ROZENTALE et al., 2020), GHISOLFI et al. (2022a) concluded that the SD models referring to the decarbonization of freight transport have strict limits to represent the system. In this context, and using a qualitative approach of causal loop diagrams, GHISOLFI et al. (2022b) presented a broad model that integrates five different decarbonization strategies, showing their affinities and synergies within the system. This model shows the importance of policymakers approaching the decarbonization problem collaboratively and systemically, avoiding their actions being offset due to feedback loops within the system.

Another conclusion from the literature review (GHISOLFI et al., 2022a) is the lack of transparency regarding the temporal dimension of the SD empirical models. The assumptions about the delays of each action to reach the results are not clear. This is an issue since time is crucial to evaluate the potential and success of policies for achieving decarbonization targets within defined timeframes. As an exception, NASSAR (2021) analyzed the empirical time factors related to the choice and change of transport mode in a Brazilian case study. By interviewing different experts, who revealed their perspectives regarding the dynamics involved in the process of infrastructure construction and transport mode choice, the author drew up three scenarios in which the time range from 13 to 22 years for companies to shift transport modes.

From the exposed background, this chapter proposes a quantitative SD model to analyze the impact of decarbonization policies made at different points in time over the reduction of freight transport emissions. SD was the chosen method since we aim to analyze policy decisions in a large-scale system that takes into account the dynamics of the system's multiple feedback loops. The proposed model helps to start filling the gaps found in the literature review carried out by GHISOLFI et al., (2022a) and presented in Chapter 2, regarding a model with multiple policy measures in a system-wide perspective and deepening the knowledge about the temporal factor that governs the dynamics of the system's responses.

4.3 Material and Methods

This section brings a geographical background to contextualize the case study regarding the Brazilian freight transport system to which the model is applied; a qualitative research with some stakeholders to investigate the main barriers, challenges, and opportunities for alternative fuel vehicles adoption in the Brazilian automotive market. Such qualitative research aimed to inspect the temporal factor related to policies promoting alternative fuel vehicles, an important input for the proposed SD model; the development of the mathematical SD model itself, data used, and the performed model tests and sensitivity analysis.

4.3.1 Geographical background

The Brazilian freight transport system has been chosen as the case study to test the applicability of this research's modeling approach. With an area of 8.5 million square kilometers, Brazil has the challenge of creating and maintaining an immense transport network to transport its products and allow the mobility of the population, which becomes complex in an ecosystem formed by different biomes, in which the need for environmental protection contrasts with economic development and the advancement of infrastructure. The Brazilian freight transport matrix is heavily based on roadways, compared to other big regions as shown in Figure 4.1.

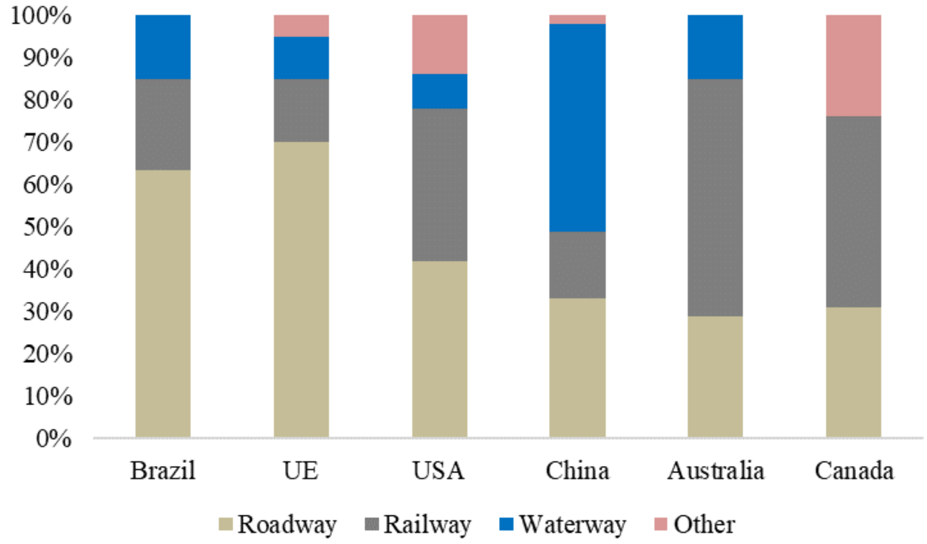

Figure 4.1 – Freight transport matrix in different countries.
Source: ENERGY RESEARCH COMPANY – EPE (2022); ITF (2022).

Table 4.1 – Commercial vehicle sales in 2021.

Global rank	Countries	Commercial vehicle sales*
1	USA	12,058,515
2	China	4,793,283
3	Canada	1,384,245
4	Japan	772,642
5	India	677,119
6	Brazil	561,384
7	Mexico	526,593
8	France	483,279
9	Thailand	436,380
10	UK	396,910

*Commercial vehicles include light commercial vehicles, heavy trucks, coaches, and buses.
Source: THE GLOBAL ECONOMY (2022).

From Figure 4.1, we can see a great opportunity for Brazil to decarbonize its freight transport by balancing the transport matrix, which can be done with investments in less emission-intensive transport, such as railways and waterways. The fact that Brazil relies on roadways to transport freight also explains the fact that it is the 6th country in the global rank of commercial vehicle sales in 2021, as shown in Table 4.1.

In terms of energy consumption, the transport sector remains highly dependent on non-renewable sources. According to the National Energy Balance – BEN (MINISTRY OF MINES AND ENERGY – MME and EPE, 2022), it was responsible for 32.5% of national energy consumption in 2021 and only road transport accounted for 30.6%. Figure 4.2 shows the high share of fossil fuels in energy consumption from the transport sector.

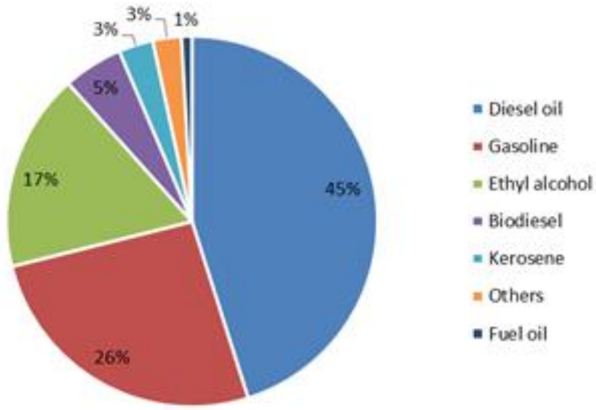

Figure 4.2 – Structure of energy consumption in the Brazilian transport sector.
Source: MME and EPE (2022).

Given the significant fossil fuel consumption in the transportation sector, it is evident the importance of the implementation of emission mitigation policies. In this sense, Brazil established several policies to encourage the production and use of biofuels, such as the National Program for the Production and Use of Biodiesel (PNPB), the National Alcohol Program (PROALCOOL) in the 1970s, and, more recently, RenovaBio, which came into force at the beginning of 2020, aiming to contribute to the regularity of supply, as well as to the competitive participation of different biofuels in the national market. In this way, the country has placed itself among the largest producers and consumers of biofuels in the world. It is noteworthy that these policies were driven by energy security issues, mainly, and environmental issues related to global warming. Also noteworthy is the Rota 2030 Program – Mobility and Logistics, launched in 2018, which establishes a series of energy efficiency, safety, and sustainability obligations for the automotive sector, with tax benefits as a counterpart for those who adhere to the program (MME and EPE, 2020).

4.3.2 Qualitative research

Qualitative research is a critical component of the overall research effort. Gathering qualitative insights from the system's stakeholders about their related decisions provides a solid conceptual foundation for our quantitative modeling.

Regarding the adoption of alternative fuel vehicles, studies on the automotive market imply four general stakeholders: freight forwarders, commercial vehicle manufacturers, energy supply systems, and the government. Freight forwarders are the customers using commercial vehicles for freight transportation, ranging from owner drivers to big companies that can be innovative (early adopters) or conservative (late adopters). Commercial vehicle manufacturers develop and offer commercial vehicles on the market and decide whether or not to invest in the development and improvement of new powertrain concepts based on expected customer demand, governmental policies, and market trends. Refueling and recharging infrastructures incorporate managers of public filling stations who decide upon their expected profitability whether they invest in alternative filling stations or not. The government sets market regulations, fuel and vehicle standards, taxes, and incentives (SEITZ, 2014; SEITZ and TERZIDIS, 2014).

Despite all the stakeholders playing an important role in the dynamics of alternative fuel vehicle adoption, in this research, we interviewed freight forwarders from the road transport sector to better understand the dynamics of their alternative fuel vehicle choices. The participants were chosen since their companies are already planning, testing, or including alternative technologies in their truck fleets. Moreover, we also interviewed a project manager in the technological innovation of Programa Rota 2030 (FUNDEP, 2023). The semi-structured interview allowed the interviewees to complement their perspectives and experiences, also encouraging them to raise issues that were not included initially in the interview schedule (FIGGOU and PAVLOPOULOS, 2015). The interviews were carried out in May and June 2022 through virtual meetings with each interviewee individually with an average duration of one hour.

When working with System Dynamics modeling, it is important to account for the system's delays and the impact they have on how the system evolves. The interviews focused on identifying and understanding the main time lags in the buying decision process of alternative fuel vehicles. The analysis revealed the need to better understand the user's perspective, comprehend what they consider necessary when choosing new vehicles, how they include technology innovation and sustainability into their strategic planning, and how willing they are to shift from one technology to another.

The interviews investigated which factors contribute to the decision-making process and raised some insights into the timing for alternative fuel vehicle adoption by early adopter companies. The experts interviewed can be seen in Table 4.2. To ensure that interviewees provided frank opinions, we have committed to keeping their identities and affiliations confidential.

Table 4.2 – Interviewees overall.

Identification	**Headquarters location**
Carrier 1	Apucarana/PR
Carrier 2	Guarulhos/SP
Carrier 3	Itajaí/SC
Carrier 4	Guarulhos/SP; Itajaí/SC; Rio de Janeiro/RJ; Cariacica/ES
Carrier 5	Contagem/MG; Parauapebas/PA; São Paulo/SP
Carrier 6	Dois Córregos/SP
Rota 2030 – Project Manager (FUNDEP)	-

The companies interviewed have fleets that range from 10 to 200 vehicles with an average age between three and nine years. The frequency of reviewing strategic decisions on fleet management occurs every six months in all the companies interviewed. The criteria for the replacement and acquisition of new vehicles by carriers can be seen in Table 4.3.

Table 4.3 – Factors that influence scrapping and the purchase of new vehicles.

Factors		**Carriers**					
		1	**2**	**3**	**4**	**5**	**6**
Vehicle replacement	Mileage	x	x			x	x
	Age	x		x	x	x	
	Maintenance cost					x	x
Purchase of new vehicles	Purchase cost	x	x	x		x	
	Maintenance cost	x		x	x	x	x
	Energy efficiency		x	x	x	x	x
	Refueling facilities				x		
	Brand	x					
	Embedded technology						x

The main factors that influence the vehicle's scrapping are the mileage traveled and its age. Secondly to the first two, the cost of vehicle maintenance is also a concern for managers and it is considered important in the decision to change the truck. The factors that influence the choice and acquisition of new vehicles are mainly purchase cost, maintenance cost, and efficiency. However, the refueling/recharging facilities, brand, and embedded technology were also indicated.

As already mentioned, the companies interviewed are in the process of planning for acquisition or have already acquired alternative technologies to the internal combustion engine, these being the truck powered by compressed natural gas (CNG) or biomethane and the electric vehicle for urban delivery. Table 4.4 shows technologies and acquisition times (real or estimated from the beginning of the planning process to the actual purchase of the vehicle) by each company.

Table 4.4 – Times of acquisition/adaptation of each alternative fuel vehicle.

		Carrier 1	Carrier 2	Carrier 3	Carrier 4	Carrier 5	Carrier 6
Alternative energy source	CNG/ biomethane	x*			x		x
	Electricity		x*	x*		x	x
Acquisition time (months)		24	12	24	24	1	8

*In process of planning for acquisition. In these cases, the time is estimated.

Carrier 1 has been studying and negotiating for about one year to obtain a CNG-powered truck to meet demand on a specific route, in which it is possible to supply it at two different stations. The company estimates that it will take two years to put the vehicle into operation. As difficulties, it was highlighted the high cost of acquisition, in addition to the challenge of supply with few stations and a long supply time.

Carrier 2 plans to purchase at least one electric van within one year. Studies are being carried out on economic feasibility, driver training, and the identification of recharging points on the routes. In addition, investment in a charging point within the company itself or allocation of the electric van on a special route where there are sufficient charging points for the autonomy of the van is considered. Among the difficulties are the high cost of acquisition, scarce charging stations, and the cost of maintenance.

Carrier 3 plans to acquire an electric van for short-distance trips, by installing its own charging point, integrated with the photovoltaic energy generation project. The steps include economic feasibility studies, installation of a photovoltaic energy generating matrix, internal negotiations, and with the car dealership, and driver training. The total estimated time to acquire the vehicle is two years, with the high purchasing cost being the main barrier. For long distances trips, autonomy is not enough and there are still no public charging stations available.

Carrier 4 has vehicles powered by CNG, with which the freight price is more expensive due to the associated costs. The acquisition process began through internal discussions, meetings with the automaker, and capturing demand from shippers. The project was made possible by the closing of longer-than-usual contracts. In addition, economic feasibility studies and route mapping were carried out to identify the refueling stations capable of meeting the demand. It is estimated that it took about two years from the initiative to the first operation of the vehicle. The company highlights the high cost of investment, the lack of tax incentives, and the bureaucracy for financing, in addition to the lack of adequate infrastructure and the long downtime for refueling.

Carrier 5 has two electric vehicles in its fleet. The company already had its generation of photovoltaic energy to supply its administrative facilities; therefore, the acquisition of vehicles was made possible by the installation of its own charging point, which took around one month. Some barriers to the acquisition included the lack of public recharging stations, limited battery life, little variety of brands and models, high acquisition cost, recharging time, and compromised vehicle autonomy due to the quality of the pavement.

Carrier 6 has vehicles powered by CNG and biomethane, in addition to electric vehicles. The latter was made possible by the installation of charging stations within the company. As main barriers, the company cites the restricted maintenance, and refueling stations without structure to receive large vehicles (CNG trucks), in addition to the lack of tax incentives. The company claims that there is a strong restriction for the full replacement of the fleet since electric vehicles are restricted to urban or short-distance trips, while CNG/biomethane-powered vehicles still do not have enough refueling infrastructure on long-distance routes.

Finally, a project coordinator linked to the Rota 2030 Program was also interviewed regarding the dynamics of the technological innovation process in the Brazilian market. The main reason for the nationalization of technological production is cost reduction, which could accelerate the decarbonization of the automotive sector. However, the country is still in the phase of acquiring knowledge and absorbing new technologies, with the degree of technological maturity being the main discrepancy between the Brazilian and international contexts. The market position of foreign companies is guaranteed by the high technological level, in addition to the continuous investment in development and innovation, which does not occur in the domestic market. The main difficulties related to technological innovation at the national level involve excessive bureaucracy and scarce resources. In general, the average product development time is two years. The time varies from four to six years adding the stages of testing, approvals, product engineering, and market launch.

The presented interviews have been important to deepen knowledge about the barriers, challenges, and difficulties faced by the road freight sector in the adoption of alternative fuel vehicles in Brazil. Regardless of the size of the companies interviewed and the territorial scope in which they operate, two main problems were highlighted by all of them: the high purchase cost and the difficulty in recharging/supplying. Some companies install their own clean energy generation networks, given the economic unfeasibility of using the conventional electrical grid, in addition to the scarce or complete absence of public charging points. For long-distance transport, the use of CNG or biomethane is also restricted by the availability of recharging stations along the routes due to the logistical difficulties of transporting these gases.

Therefore, the acquisition time of alternative technologies by the companies interviewed must be analyzed considering that they are early adopters and that they act without the collaboration of other sectors, although the last is considered imperative for the introduction of new technologies on a large scale in the market, such as the energy, regulatory, and infrastructure sectors. We believe that, as these sectors become involved in the process and facilitate the access by transport companies, the technologies' acquisition times will be reduced. However, uncertainty remains about the time frame for the involvement of other sectors.

Thus, the time factor of the policy for promoting alternative fuel vehicles, in the model presented in the next section, is based on projections from a study carried out by the Boston Consulting Group - BCG together with the Brazilian National Association of Automotive Vehicle Manufacturers – ANFAVEA (BCG and ANFAVEA, 2021), which considers several forces influencing the evolution of the adoption of vehicle technologies, such as government regulation and incentives, pressure from investors and customers for environmental, social and governance (ESG) principles, technological feasibility and development of industry, availability of energy production and distribution infrastructure, and the vehicle's total cost of ownership.

4.3.3 Quantitative SD modeling and data used

The approach used to model the dynamics of freight transport decarbonization policies is based on an SD conceptual model represented by causal loop diagrams (GHISOLFI et al., 2022b; see also Chapter 3). This conceptual model is composed of five submodels, each one representing the dynamics of a specific decarbonization strategy: reducing freight transport demand, shifting freight to low carbon-intensity modes, improving vehicle utilization, increasing energy efficiency, and promoting new energy sources. The submodels are interrelated through feedback loops. We highlight that, despite being based on the causal loop diagrams presented by GHISOLFI et al. (2022b), the present simulation model has some assumptions and simplifications: the freight transport demand is an input variable, based on historical series, instead of being internally modeled; vehicle utilization, used to estimate the ideal fleet size, is based on an input variable that accounts for the transport activity carried out by vehicles; the energy efficiency, used to estimate the different energy consumptions, is also based on input data. On the other hand, the strategies of shifting freight to low carbon-intensity modes, and promoting new energy sources, are modeled as dynamic levers from a policy perspective. As part of the strategy of promoting new energy sources, the fleet renewal process is dynamically modeled by the SD aging chain structure (STERMAN, 2000). The choice of the simulated strategy regarding new energy sources is justified by the fact that it is the only policy measure that can really decarbonize the freight system, as far as the energy sources are clean, while the other four strategies can only mitigate the freight transport emissions. The other considered decarbonization policy is related to the choice of more efficient modes of transport, as it has a huge potential for improvements in our case study context.

Thus, the simulation model is organized into three submodels, as presented in the next subsections, each one presenting the stock and flow diagrams and their main equations. The model was developed in Vensim® Pro (VENTANA SYSTEMS, 2022), and the simulation timeframe range from 2020 to 2050. All detailed equations can be found in Appendix A.

4.3.3.1 Ideal fleet size

The first submodel aims to simulate the ideal fleet size based on the activity assigned to each transport mode. Figure 4.3 shows the stock and flow diagram of this submodel.

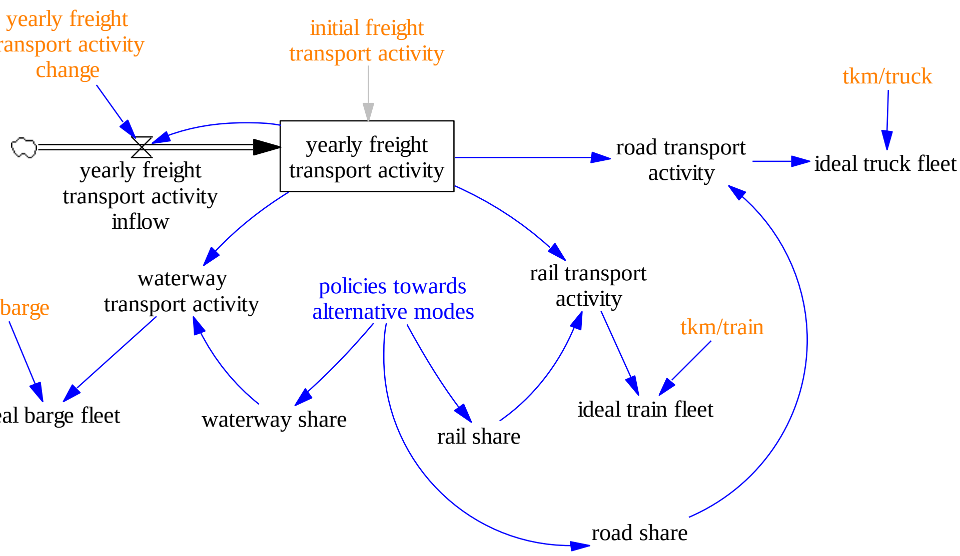

Figure 4.3 – Ideal fleet size submodel.

The simulation starts with the stock and flow variables regarding the yearly freight transport activity, measured in tonne-kilometers (tkm)[1], which depends on the freight transport activity of the initial year of the simulation, in addition to an average percentage of the future variation, based on historical series, as shown in Figure 4.4.

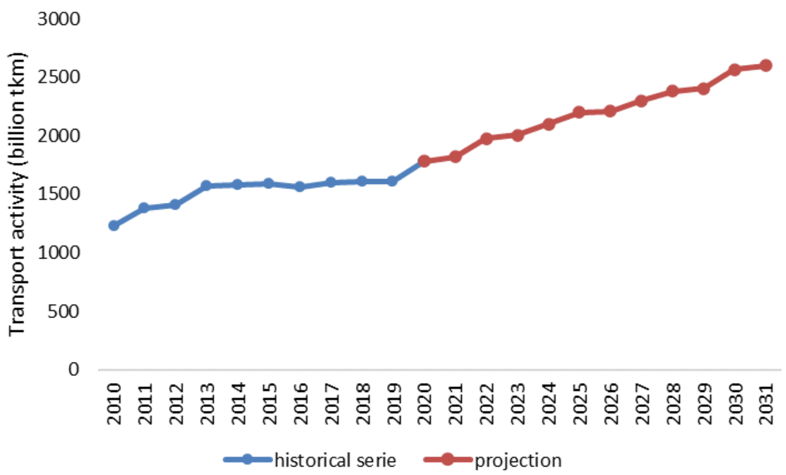

Figure 4.4 – Historical series and projection of freight transport activity.
Source: Brazilian Energy Research Company (EPE, 2022).

The next step is the mode split, simulating the percentage of freight that will be carried by roadways, railways, or waterways. This is based on Brazilian's National Logistics Plan – NLP 2035 (MINISTRY OF INFRASTRUCTURE and BRAZILIAN ENTERPRISE FOR PLANNING AND LOGISTICS – EPL, 2021) which, by predicting a set of

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[1] Tonne-kilometers (tkm) – unit of measurement of goods transport which represents the transport of one tonne of goods over a distance of one kilometer.

investments in national logistics infrastructure over the next years, simulates scenarios with different levels of achievement of the proposed goals, and consequently the use of the modal matrix. The NLP 2035 is then an infrastructure investment plan, which is modeled here by the ramp function. This function smoothly changes the variable value as a curve and its use is common in situations where it is necessary to simulate a linearly increasing or decreasing flow that is not constant over time (ABIDIN et al., 2014). The ramp function assigns zero to the variable until the beginning of its behavior change. After this period, the curve changes the variable value until it reaches a predicted value and then remains constant. Thus, this function allows the simulation of the adaptation period of new policies (COYLE, 1996). During the simulation period, the level of NLP 2035 implementation starts in 2020 and will increase linearly to reach 100% by 2035. Therefore, the NLP is defined in Equation (4.1)

$$policies\ towards\ alternative\ modes = RAMP(0.0666667, 2020, 2035) \tag{4.1}$$

Based on the initial percentage and the NLP 2035 projections for the modal share, an S-shaped curve represents the relationship between the modal share and the level of NLP implementation. The initial percentage of use of each mode is 63.3%, 21.7%, and 14.9% for road, rail, and waterways, respectively. In the case of complete fulfillment of the NLP, Table 4.5 presents the projections for each scenario considering the freight modal share. As highlighted before, each scenario of NLP 2035 represents a set of logistics infrastructure investments, i.e., on strategic railway corridors, waterways, ports, multimodal integration, etc., which have the potential to change the modal share of the freight transport system if implemented.

Table 4.5 – Initial modal share and projections for 2035.

Modes	**2020**	**Modal share – Scenarios 2035**		
		1	**2**	**3**
Roadway	63.3	55	40	32
Railway	21.7	31	43	47
Waterway	14.9	13	16	19

Source: EPE (2022); MINISTRY OF INFRASTRUCTURE and EPL (2021).

The dependency between the NLP implementation and the modal share is modeled through an S-shaped curve with the general form of Equation (4.2).

$$modal\ share = a\ x \tanh(b\ x\ NLP + c) + d \tag{4.2}$$

where a, b, c, d are scale parameters and NLP represents the policies toward alternative modes, which is a percentage of its implementation (0% refers to no implementation and

100% refers to the full implementation). The attainment of these values would occur according to an initially slow behavior. Once the initial competencies of policy have been exceeded, the growth becomes exponential until a reversal in the implementation rate stabilizes at the end of the NLP implementation. As an example, the rail share in Scenario 3 of NLP 2035 is defined by Equation (4.3) and illustrated in Figure 4.5. The other equations for modal share as a function of policies toward alternative modes are provided in Appendix B.

$$Rail\ share = 0.05\ x\ \tanh(15\ x\ policies\ towards\ alternative\ modes - 7.5) + 0.26 \tag{4.3}$$

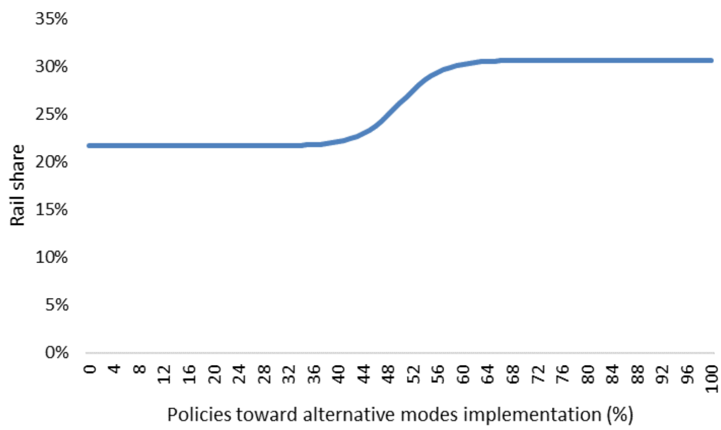

Figure 4.5 – Relationship between rail share and policies toward alternative modes.

The choice of the sigmoid function to represent the mode share is due to the behavior of policy implementation whose growth is exponential at first but gradually decreases until the system reaches its equilibrium level, commonly observed in SD (STERMAN, 2000) and already applied in transportation studies (FONTOURA et al., 2019; 2020; GEORGIADIS and VLACHOS, 2004).

Given the freight transport activity forecast and the percentage of freight being transported by each mode, we have the freight transport activity by mode. The next step is to simulate the ideal fleets of trucks, trains, and barges. As an example, the ideal truck fleet is given by Equation (4.4).

$$ideal\ truck\ fleet\ = \frac{road\ transport\ activity}{actual\ tkm/truck} \tag{4.4}$$

The variables “actual tkm/truck”, “actual tkm/train”, and “actual tkm/barge” represent the efficiency index to be maintained concerning the fleet usage. Such indexes are based on the assumption that the vehicles will perform the same transport activity (measured in tkm) in the future. To calculate these input data, we have used the historical series of transport activity (tkm) by mode given by EPE (2022), the historical series of the road fleet given by SINDIPEÇAS and ABIPEÇAS (2022), and the historical series of the rail and waterway fleets obtained from the CNT Transport Yearbook (CNT, 2021). The ideal fleets are used in the Vehicle choice submodel for the dynamics of the fleet renewal process.

4.3.3.2 Vehicle choice

The second submodel aims to simulate the market share of different options of vehicle technology and fuels that will integrate each transport mode fleet. Figure 4.6 shows the diagram of the total truck fleet composed of old and new trucks powered by diesel/biodiesel, electricity, hydrogen, and CNG/biomethane. We highlight that the old fleet is only powered by diesel/biodiesel.

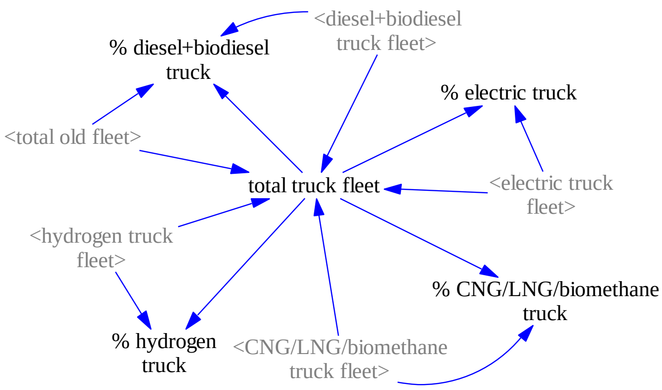

Figure 4.6 – Total truck fleet diagram[2].

We have segregated the old fleet from the new fleet since their stock-and-flow structures are different: while the new fleet has an inflow of vehicles coming from vehicles' sales, the old fleet has only outflows represented by the scrappage rate. The old fleet is composed of stocks of vehicles already in the market in the first year of the simulation. In Figure 4.7, each stock represents the sum of the trucks of a certain age group (six-year range) that are still being used. We have chosen to group the vehicles by age every six years, instead of modeling each age by an individual stock, given that the Brazilian fleet has vehicles over 40 years old still in use. The age distribution of the active fleet of trucks, locomotives, and barges in the first year of the simulation is given by SINDIPEÇAS and ABIPEÇAS (2022), BNDES (2014) and CNT (2021), respectively.

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[2] The shadow variables (in gray) have been defined in other parts of the diagram and are used to let it visually clean, besides connecting different submodels (placed in different views).

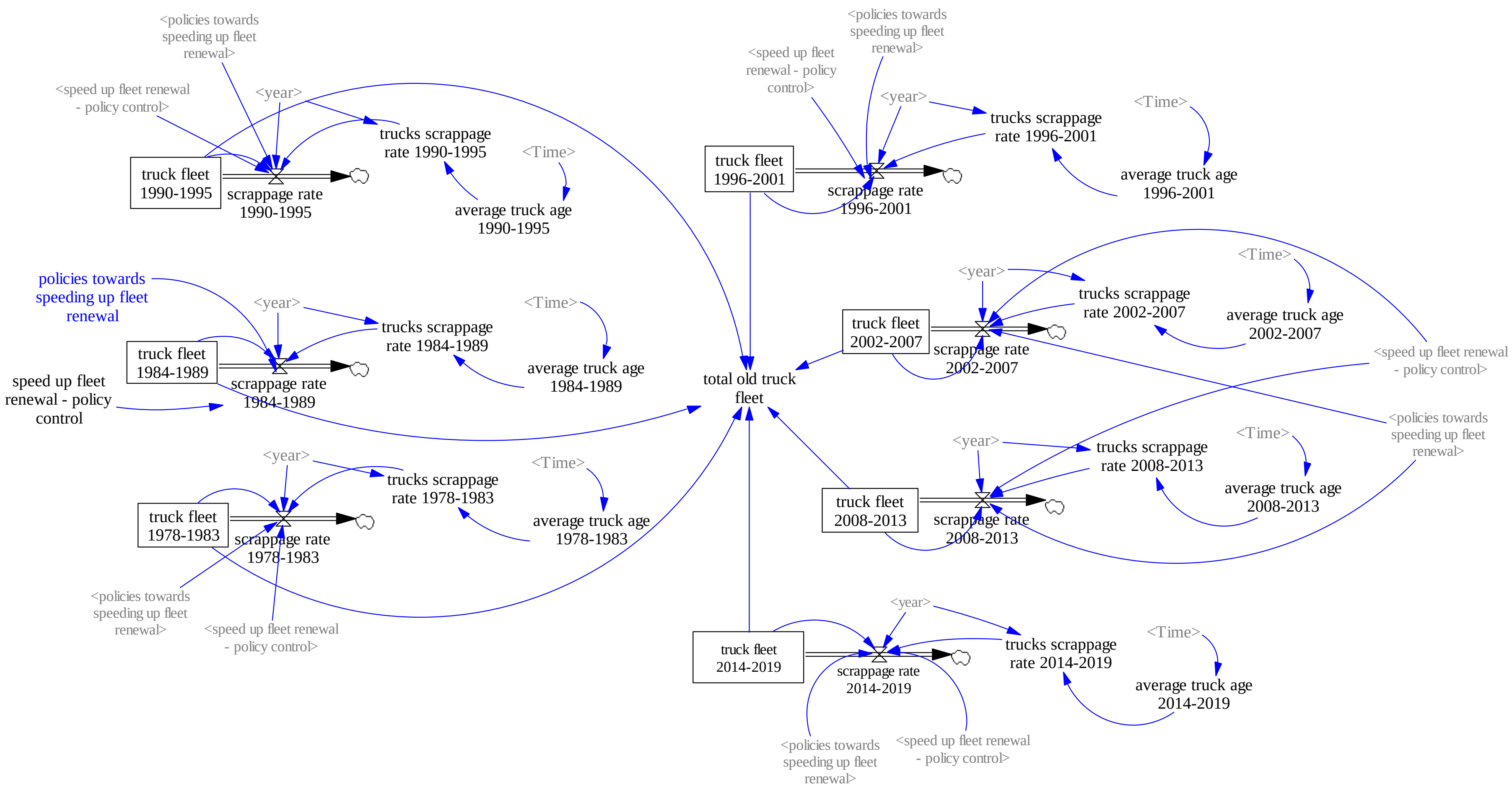


Figure 4.7 – Total old truck fleet.

There are two policy-related variables: “speed up fleet renewal-policy control” and “policies towards speeding up fleet renewal”. The first one assumes zero or one, according to the scenario where these policies are active or not. The second one is given by Equation (4.5), assuming that this policy will be applied in a time range of five years.

$$policies\ towards\ speeding\ up\ fleet\ renewal = RAMP\ (0.2, 2020, 2025) \tag{4.5}$$

As the fleet ages, vehicles are scrapped, as indicated by the scrappage rate in Equation (4.6).

$$\begin{gathered} scrappage\ rate = IF\ THEN\ ELSE(speed\ up\ fleet\ renewal - policy\ control = \\ 0, truck\ fleet\ x\ trucks\ scrappage\ rate, (1 + \\ policies\ towards\ speeding\ up\ fleet\ renewal) x\ truck\ fleet\ x\ trucks\ scrappage\ rate) \end{gathered} \tag{4.6}$$

If the policy towards speeding up fleet renewal is applied, the scrappage rate will be accelerated by this policy, otherwise, it will occur at the normal rate, described as follows. The truck scrappage rate function was calibrated by the Brazilian National Traffic Department – DENATRAN (MINISTRY OF THE ENVIRONMENT, 2014) using average age and total fleet data. The resulting scrapping function is a renormalized logistics function defined by Equation (4.7).

$$S(t) = 1 - \left[\frac{1}{1 + exp\ (a(t - t_0))} + \frac{1}{1 + exp\ (a(t + t_0))}\right] \tag{4.7}$$

with:

- $S(t)$ is the portion of scrapped trucks;
- t is the trucks’ age in years;
- t_0 is 17.0 for trucks; and
- a is 0.10 for trucks.

Given the lack of data for the locomotives scrappage function definition in Brazil, for locomotives scrappage, we have used the function defined by GREENE et al. (2004) regarding the American locomotive fleet, as shown in Equation (4.8).

$$S(t) = 1 - \frac{EXP(\frac{b - t}{a}) + EXP(\frac{2b - t}{a})}{EXP(\frac{b}{a}) + EXP(\frac{2b - t}{a})} \tag{4.8}$$

with:

- $S(t)$ is the portion of scrapped locomotives;
- t is the locomotive’s age in years;
- a is 7.971970; and

- b is 25.45011.

The same lack of data occurs for the Brazilian barge fleet, which leads us to use the ship fleet scrappage function defined by HELD et al. (2021), shown in Equation (4.9).

$$S(t) = 1 - (1 + EXP(a1\ x\ t - a2))^{-b} \tag{4.9}$$

with:

- $S(t)$ is the portion of scrapped barges;
- t is the barge's age in years;
- $a1$ is 0.4105;
- $a2$ is 9.2562; and
- b is 0.2320.

Surviving and scrapping rate curves for trucks, locomotives, and barges are shown in Figure 4.8.

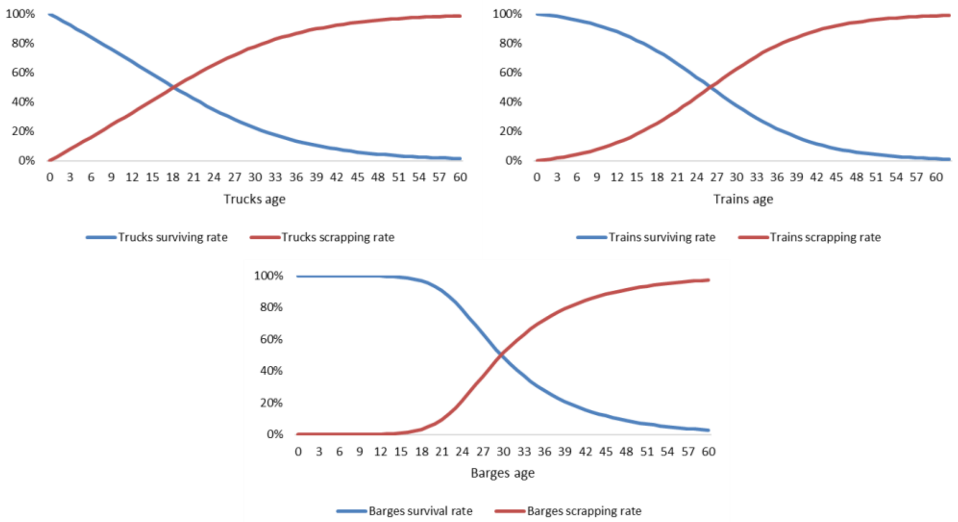


Figure 4.8 – Trucks, trains, and barges surviving and scrapping curves.

As the old fleet will be scrapped over time, new vehicles must enter the market. This fleet renewal process is modeled by the aging chain mechanism, which is used to represent situations where the outflows of items in a stock and flow structure are age-dependent and allow to model changes (through inflows and outflows) of any intermediate stock of the aging chain structure (STERMAN, 2000). Thus, we have assumed that the rate at which companies discard and replace their fleets strongly depends on the age of their vehicles and that the scrappage rates are based on the probabilities given by Equations (4.7), (4.8), and (4.9). Figure 4.9 shows the aging chain structure for the fleet renewal process.

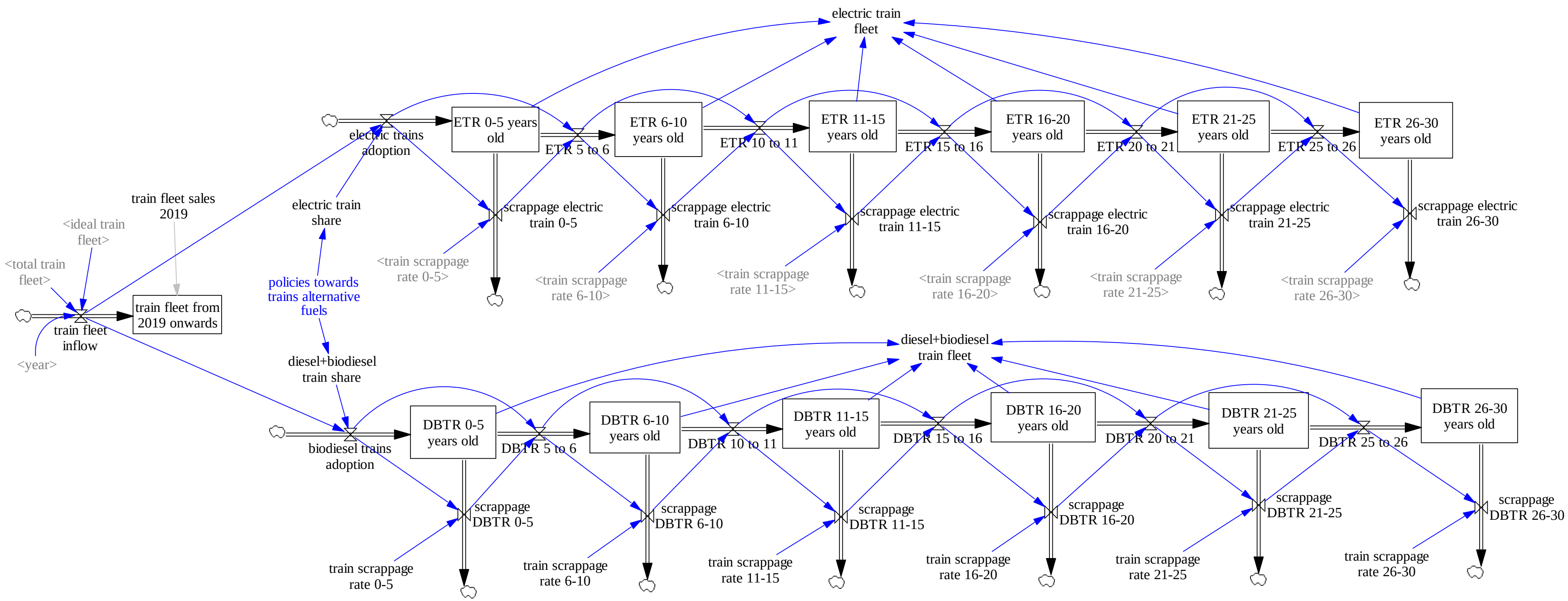


Figure 4.9 – Aging chain structure for the fleet renewal process.

The truck fleet inflow (Figure 4.10) indicates the adoption of new vehicles, based on the total truck fleet (described in Figure 4.6 of this submodel), and the ideal truck fleet (described in Figure 4.3 of the Ideal fleet size submodel), as exemplified by Equation (4.10).

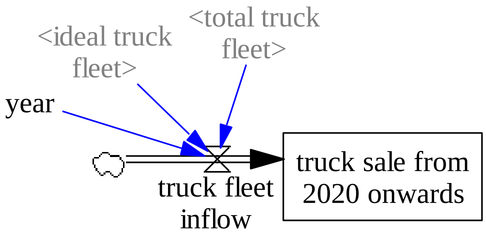


Figure 4.10 – New truck sales.

$$truck\ fleet\ inflow = IF\ THEN\ ELSE(total\ truck\ fleet < ideal\ truck\ fleet, (ideal\ truck\ fleet - total\ truck\ fleet), 0) \tag{4.10}$$

The next step involves the simulation of the share of each vehicle's propulsion technology. From the first year of the simulation onwards, the vehicle fleet is split between different powering systems, according to specific policies towards alternative fuels. Regarding trucks, this is based on a technical study developed by Boston Consulting Group – BCG and the Brazilian Association of Motor Vehicle Manufacturers – ANFAVEA (BCG and ANFAVEA, 2021) which predicts that the decarbonization of the automotive sector in Brazil will be driven by several forces, such as tighter regulations, pressure from investors and customers, industry and technology development, increased availability of infrastructure and reduced total cost of vehicle ownership. The interaction of these forces will shape different decarbonization routes in Brazil in the coming years. This study is represented in the model by the variable "policies towards trucks alternative fuels", which is modeled by the ramp function to simulate the period of adaptation to the policies and implementation of actions. During the simulation period, the level of policy implementation will increase linearly to reach 100% by 2035, as defined in Equation (4.11).

$$policies\ towards\ trucks\ alternative\ fuels = RAMP(0.0666667, 2020, 2035) \tag{4.11}$$

The scenarios predicted by BCG and ANFAVEA (2021), regarding the projections for the percentage of use of each type of fuel for trucks are presented in Table 4.6.

Table 4.6 – Initial fuel share for trucks and projections for 2035.

Fuels	2020	Fuel share (%) – Scenarios 2035			
		1	2	3	4
Diesel	100	86	68	82	70
Biodiesel	-	-	-	18	30
Natural gas/biomethane	0	7	10	-	-
Electricity	0	7	15	-	-
Hydrogen	0	0	7	-	-

Source: BCG and ANFAVEA (2021).

Scenarios 1 and 2 simulate the introduction of alternative fuels (natural gas/biomethane, electricity, and hydrogen) at different shares. Scenarios 3 and 4 simulate the percentage of biodiesel in diesel blends. In the model, these scenarios are modeled by an S-shaped curve that represents the relationship between the fuel share and the level of policy implementation, as shown in Equation (4.12) for electric trucks in Scenario 1. The other equations for each fuel and scenario are presented in Appendix B.

$$electric\ truck\ share = 0.035\ x\ \tanh\left(15\ x\ policies\ towards\ multimodal\ transport - 7.5\right) + 0.035 \tag{4.12}$$

For trains and barges, there are no studies or government plans for such policies toward alternative fuels. However, we considered independent initiatives announced by some concessionaires to simulate a scenario in which all modes are changing to a more sustainable outline. In this case, Table 4.7 shows the set of addressed scenarios for 2050.

Table 4.7 – Initial fuel share for trains and barges and projections for 2050.

Fuels	2020	Fuel share (%) – Scenarios 2050	
		1	2
Diesel	100	50	0
Electricity	0	50	100

Source: VLI (2022); RUMO (2022); VALE (2022).

The next step of this submodel is the aging chain of new vehicles sold from 2020 onwards, a sequence of stocks for each age range of five years (Figure 4.9). Each year, newly sold vehicles enter the first stock and remain there for five years, being scrapped according to the respective scrapping rate Equations (4.7), (4.8), and (4.9) for trucks, trains, and barges, respectively, considering the average age of the age group. The flow variables linking the stocks are defined as a fixed delay function that ensures that vehicles only go to the next age group's inventory at the end of five years. As an example, the outflow of the diesel/biodiesel trucks aging from five to six years old is defined in Equation (4.13).

$$DB\ 5\ to\ 6 = DELAY\ FIXED(biodiesel\ trucks\ adoption - \text{scrappage DB 0-5}, 5, 0) \tag{4.13}$$

For the new vehicles entering the market, we have modeled an aging chain of 30 years for trucks, trains, and barges. Then, the structure for each type of vehicle is composed of six stocks, each one of them with a five years range.

With the total fleet and the fleet technology share, the next submodel simulates energy consumption and emissions from the freight transport sector.

4.3.3.3 Energy consumption and emissions

The last submodel aims to simulate the consumption of each type of fuel/energy and emissions, using the results of the previous submodels, referring to the freight transport activity by mode and percentage of each vehicle's technology in the fleet. We have assumed that the amount of transport activity performed by each vehicle technology will be proportional to their fleet market share. Figure 4.11 shows the diagram related to the energy consumption of the truck fleet.

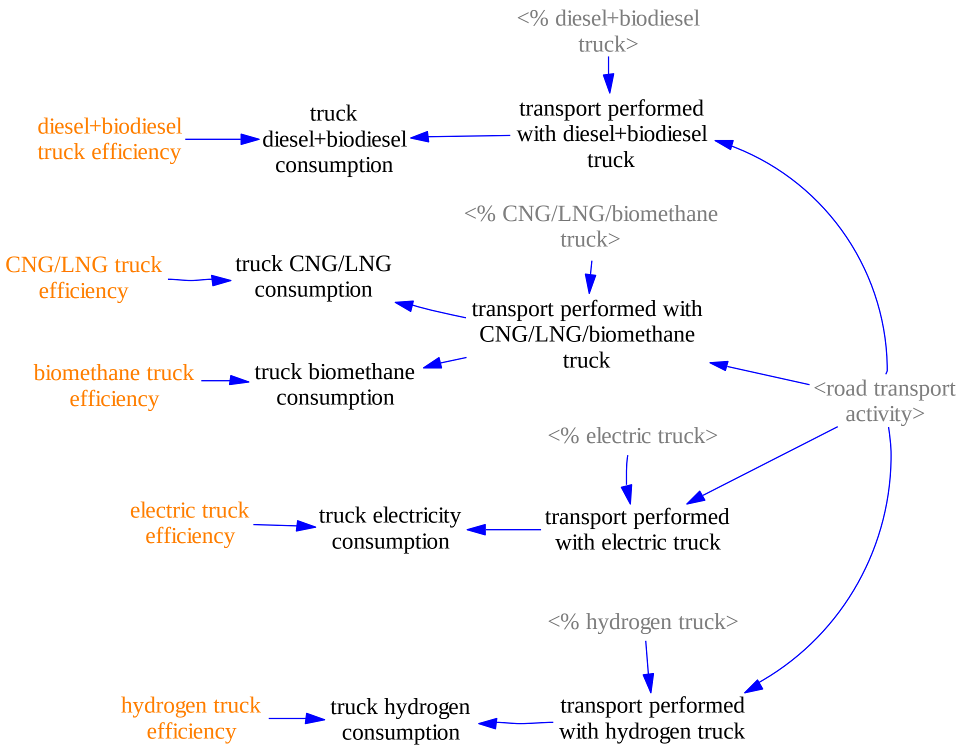


Figure 4.11 – Energy consumption submodel – trucks fleet.

The energy consumption is given by the transport activity performed with each type of fuel vehicle and its efficiency, as exemplified by Equation (4.14). The energy efficiency data is presented in Table 4.8.

$$\begin{aligned} &truck\ electricity\ consumption \\ &= \ transport\ performed\ with\ electric\ truck\ x\ electric\ truck\ efficiency \end{aligned} \tag{4.14}$$

Figure 4.12 shows the last part of the submodel, regarding the simulation of CO_2 emissions for each transport mode.

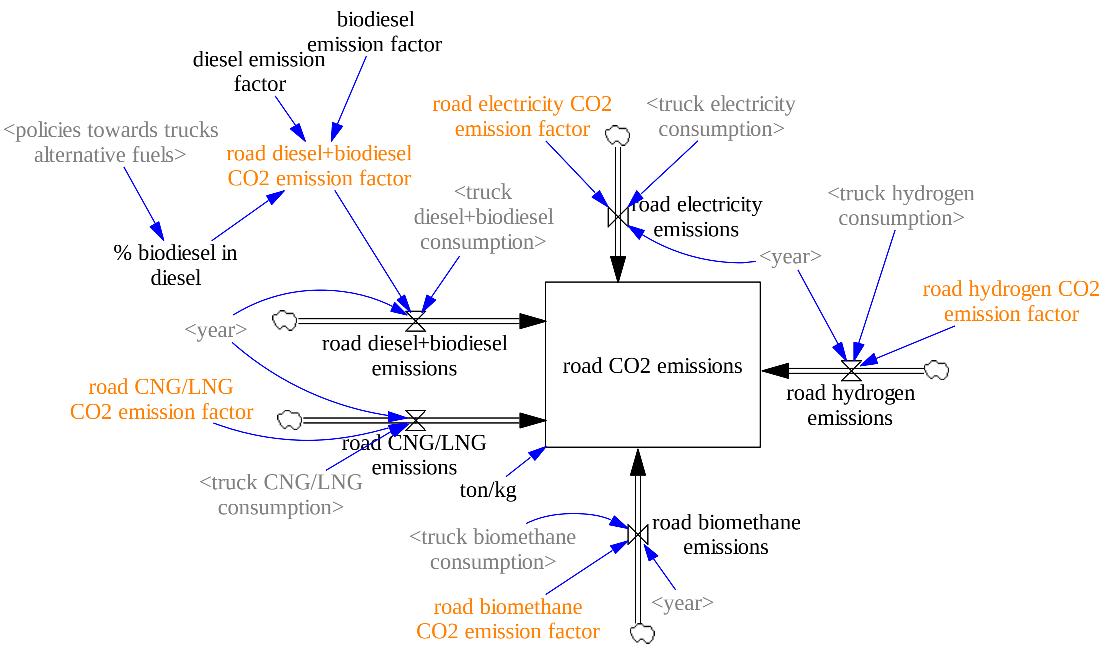


Figure 4.12 – Emissions submodel – trucks fleet.

The emissions inflows are given by the fuel/energy consumption and the related CO_2 emission factor, as shown in Equation (4.15) for the case of road hydrogen emissions.

$$\begin{gathered} road\ hydrogen\ emissions\ = \\ truck\ hydrogen\ consumption\ x\ road\ hydrogen\ CO_2 emission\ factor \end{gathered} \tag{4.15}$$

Emissions rates are accumulated in a stock variable for each transport mode. Then, the emissions stocks are aggregated to estimate total emissions from freight transport. The data regarding efficiency and emission factors for each vehicle type and propulsion energy are given in Table 4.8.

To maintain a fair comparison between the different energy sources, we have considered only the tank-to-wheel energy use, which explains the null emissions factors for electricity and hydrogen. Another pertinent approach could be the life cycle analysis (well-to-wheel) of the energy sources considered, showing how clean alternative energies are for each case study.

Table 4.8 – Efficiency and CO_2 emission factor for vehicles and propulsion energy options.

Vehicle	**Propulsion energy**	**Energy efficiency factor**	**Source**	**CO_2 emission factor**	**Source**
Truck	Diesel	0.0577 l/tkm	MINISTRY OF MINES AND ENERGY – MME et al. (2020)	2.697 kg/l	GREENHOUSE GAS PROTOCOL (2021)
	Biodiesel	0.0577 l/tkm	MME et al. (2020)	2.431 kg/l	MINISTRY OF THE ENVIRONMENT (2014)
	CNG	0.0629 m³/tkm	MME et al. (2020)	2.101 kg/m³	FERREIRA (2022)
	Biomethane	0.0629 m³/tkm	MME et al. (2020)	0.24 kg/m³	FERREIRA (2022)
	Electricity	1.35 kWh/tkm	MERCEDES-BENZ (2022); VOLVO (2022)	0	-
	Hydrogen	0.10 kg/tkm	HYZON (2022)	0	-
Train	Diesel	0.0047 l/tkm	EPL and INSTITUTE OF ENERGY AND ENVIRONMENT-IEMA (2021)	2.697 kg/l	GREENHOUSE GAS PROTOCOL (2021)
	Electricity	53.1 Wh/tkm	ĆWIL et al. (2021)	0	-
Barge	Diesel	0.0038 l/tkm	EPL and IEMA (2021);	2.697 kg/l	GREENHOUSE GAS PROTOCOL (2021)
	Electricity	28 Wh/tkm	BAZALUK et al. (2021)	0	-

The last part of the model, shown in Figure 4.13, simulates a "control" variable by comparing the total freight emissions with estimated budgets for the sector. Given the absence of a target to reduce emissions from the Brazilian freight transport sector, the budgets are estimated based on the percentage of Brazilian freight emissions and the CO_2 emission budgets for limiting global warming to 1,5°C or 2°C by 2050. The percentage of Brazilian freight emissions is calculated based on the data of emissions from the sector in 2020 out of the global CO_2 emissions in the same year. Equation (4.16) presents the definition of the proposed CO_2 emissions budget for the Brazilian freight transport sector for limiting global warming to 1.5°C. The freight emissions budget for limiting global warming to 2ºC is similar. These proposed budgets allocate to the Brazilian freight transport sector a percentage of the global emissions budget equivalent to its percentage of emissions in 2020 as the emissions right in the following years.

$$\begin{aligned} &\%\, budget\ 1.5°\, C\ Brazilian\ freight \\ &\quad = global\ CO2\ budget\ 1.5°C" * "\%\, Brazilian\ freight\ emissions" \end{aligned} \tag{4.16}$$

These estimated budgets are debatable and will be better argued in the Discussions section (Section 4.5). The input data is shown in Table 4.9.

Table 4.9 – Data related to transport emissions control.

Variable	Data input	Source
Global CO_2 emissions 2020	$34{,}81 \times 10^9$ ton	STATISTA (2022)
Brazilian freight transport emissions 2020	$79{,}7 \times 10^6$ ton	EPE (2022); EPL and IEMA (2021)
CO_2 budget 1,5°C	400×10^9 ton	INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE (IPCC, 2021)
CO_2 budget 2°C	1150×10^9 ton	IPCC (2021)

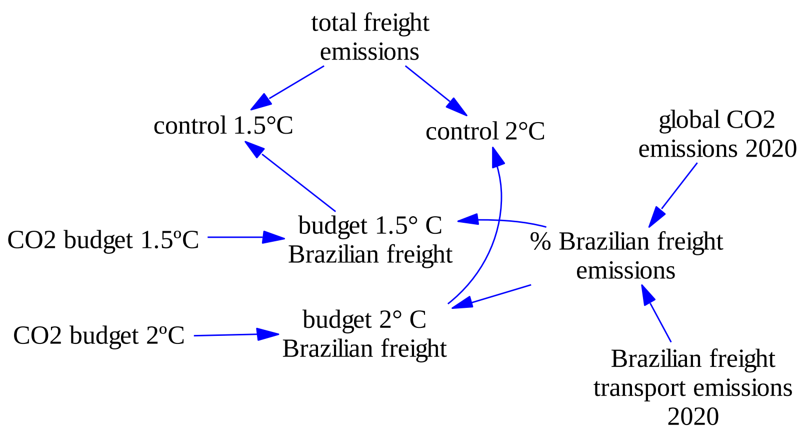


Figure 4.13 – Freight transport emissions control.

4.3.4 *Model testing and sensitivity analysis*

Confidence in system dynamics models can be increased by a wide variety of tests of model structure, model behavior, and model policy implications (FORRESTER and SENGE, 1980). Model testing focuses on the process of building confidence that a model is appropriate for its purpose. ZAGONEL and CORBERT (2006) pointed out the most appropriate tests for SD quantitative models: boundary adequacy tests, structure assessment tests (physical conservation), dimensional consistency, integration error, extreme conditions tests, and behavior reproduction tests. All these tests were performed according to STERMAN (2000). After necessary adjustments, the model performed as expected in the testing phase and was considered appropriate for simulation.

4.3.4.1 *Boundary adequacy test*

Boundary adequacy tests assess the appropriateness of the model boundary for the purpose at hand. Interviews with experts and a literature review may suggest some processes that perhaps should be made endogenous (STERMAN, 2000).

The boundaries of the model could be expanded drastically, with the inclusion of many variables found, both in the literature review and in interviews with experts. Despite being based on the causal loop diagram by GHISOLFI et al. (2022b), who presented a qualitative model with five decarbonization strategies and their basic variables, we chose to focus on the dynamics of fleet renewal and how it impacts emissions from freight transport. This factor could also have been modeled differently, in which fleet renewal policies would be analyzed based on utility functions, which would expand the model with details of the multiple factors considered by users when choosing one technological alternative over another. However, it was decided to add such factors to the policy-related variables (policies towards vehicles alternative fuels, policies towards speeding up fleet renewal, and policies towards alternative modes), which objective is not to show how (cost reduction, provision of infrastructure, increased efficiency, etc.), but rather when targets will be achieved in different scenarios. Then, the boundary of the proposed model is considered adequate for its purpose.

4.3.4.2 Structure assessment test (physical conservation)

Structure assessment focuses on the conformance of the model to basic physical realities such as conservation laws. A common violation of physical law involves stocks that cannot become negative in real quantities such as population inventories. Therefore, the outflows from all such stocks must approach zero as the stock approaches zero. This means there must be a first-order negative feedback loop that restricts all the outflows from real stocks so that the flow is zero when the stock is zero. Structure assessment tests are carried out using stock and flow diagrams, besides direct inspection of the equations (STERMAN, 2000). In the process of formulating the model, the physical conservation test was performed. Figure 4.14 shows the example of the stock of the total old truck fleet, which does not become negative, despite the absence of inflows of new vehicles into old fleet stocks.

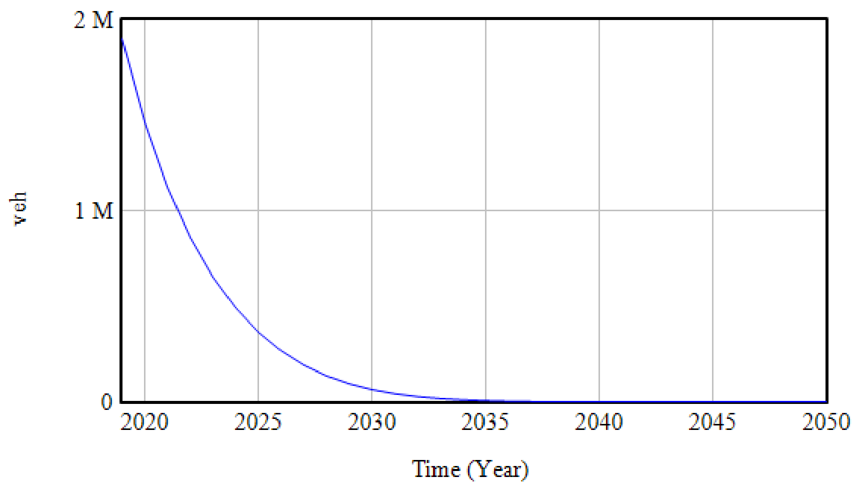


Figure 4.14 – Structure assessment test – example of the stock of the total old truck fleet.

4.3.4.3 Dimensional consistency test

The dimensional consistency test refers to the direct and systematic verification of all equations and variables to check their real meaning and unit adequacy (STERMAN, 2000). This test was performed using the units check tool available on Vensim® Pro. The inconsistencies were solved during the model formulation.

4.3.4.4 Integration error test

For the proposed model, we used the Euler integration technique, which assumption is that the rates (flow variables) remain constant between two time periods (time step dt). The assumption that the rates remain constant throughout the time interval dt is reasonable if the dynamics of the system are slow enough and dt is small enough. The definitions of "reasonable" and "small enough" depend on the accuracy required, which in turn depends on the purpose of the model[3].

Given the purpose of the model to simulate the impacts of policies over decarbonization of the freight system, which can take years, the assumption of the Euler integration technique was considered appropriate. The choice of the time step dt was made by systematically cutting the value in half and checking the significance of the change over the results. Table 4.10 shows the output values of the total CO_2 emissions from freight transport for the year 2050.

Table 4.10 – Freight CO_2 emissions in 2050 for different time steps.

Year	Time Step (year)	Emission CO_2 ($tonCO_2$)	Variation (%)
2050	1	9.71×10^9	-
	0.5	9.86×10^9	1.55
	0.25	9.94×10^9	0.78
	0.125	9.97×10^9	0.39
	0.625	9.99×10^9	0.20

Then, the chosen time step was 0.125, since the variation of its result is under 0.5%, taken as a reasonable accuracy.

4.3.4.5 Extreme conditions test

Models must be robust under extreme conditions, which means that their behavior must be realistic under any imposed conditions. The extreme conditions test verifies if the model presents an appropriate behavior when the parameters are subjected to extreme

[3] For more information about numerical integration techniques, see Appendix A of STERMAN (2000, p. 903).

values, such as zero or infinity, and can be performed considering two ways: by direct inspection of the model equations or by simulation (STERMAN, 2000). The variables submitted to extreme values for this test, as well as the expected behavior for verification, are shown in Table 4.11.

Table 4.11 – Tested variables in extreme conditions test.

Submodel	Variable	Value	Expected behavior
Ideal fleet size	Yearly freight transport activity	0 tkm	Ideal Vehicle fleet, Vehicle fleet inflow, Vehicle energy consumption, and Emissions will be null
	Yearly freight transport activity change	100%	Variable "control" will reach 1 much earlier, meaning that emissions would exceed its budget too fast
Energy consumption and emissions	Energy vehicle Efficiency	1 l/tkm	Energy consumption and emissions will be much higher
	Emissions factor	1,000 $kgCO_2/l$	Emissions will be much higher and Variable "control" will reach 1 much earlier, meaning that emissions would exceed the budget too fast

All expected behaviors under the extreme conditions established were respected, which corroborates the structure reliability of the proposed model.

4.3.4.6 Behavior reproduction test

The behavior reproduction test assesses the model's ability to reproduce the behavior of a system by using, for example, descriptive statistics to assess the point-by-point fit. The behavior reproduction test aims to uncover flaws in the structure or parameters of the model and assess whether they matter relative to the purpose. In addition to showing how well the model fits, this test also points out all the places it does not. All discrepancies should be discussed so that a consensus can be reached on whether they are significant enough to lead to model revisions (STERMAN, 2000).

This test was carried out based on the business-as-usual (BAU) scenario, which purpose is to show the dynamics of the current system. We have tested the variables yearly freight transport activity, total freight emissions (sum of road, rail, and waterway emissions), total truck fleet, and truck fleet sales, for which we have historical data series to compare the results with, as shown in Figure 4.15.

For a more complete analysis, we used validation metrics of regression models, which help in the analysis of the prediction model in comparison to the database used. Such metrics are based on the calculation of the difference between the real data and the value obtained by the model based on the baseline scenario. The metrics used were the coefficient of determination (R^2), Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Squared Error (RMSE).

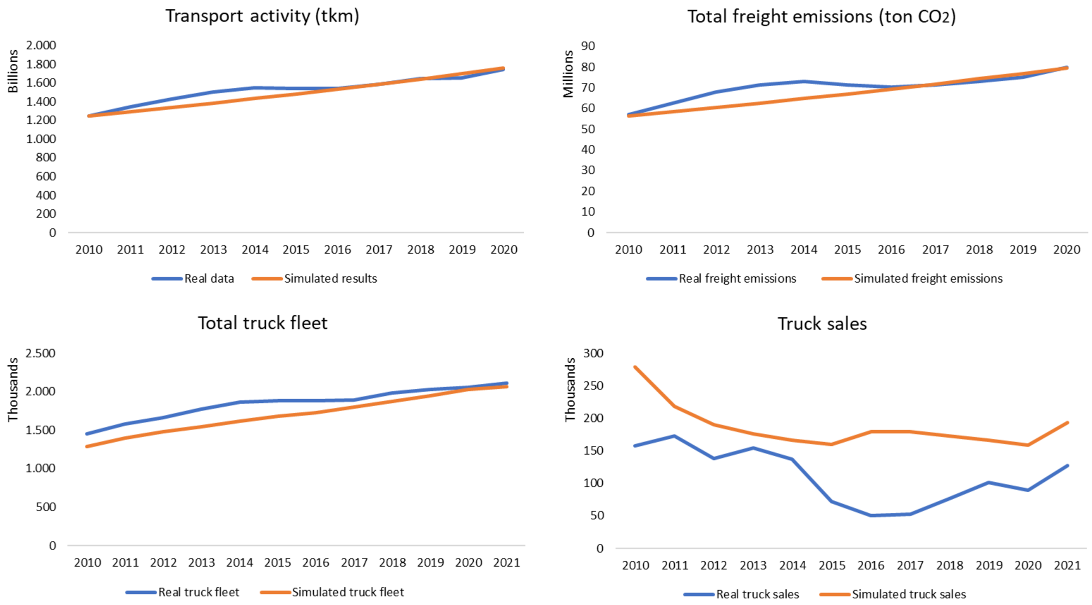


Figure 4.15 – Comparison between real data and simulated results for transport activity, total freight CO_2 emissions, total truck fleet, and truck sales.

The R^2 metric represents the percentage of data variance that is explained by the model. In this sense, the closer the value of R^2 is to 100%, the more explanatory the model is about the data obtained in the simulation. MAPE is a metric that demonstrates the percentage of error concerning actual values. Thus, the higher this percentage, the greater the average difference between the real values and those simulated by the model. The MAD represents the average of the distances between each simulated value and the mean value of the real data, indicating the variability of the simulated values. The RMSE demonstrates the difference between the simulated and the real value, however, penalizing the outliers, i.e., those simulated values that are farther from the real ones (CEYLAN, 2020). Table 4.12 shows the R^2, the MAPE, the MAD, and the RMSE between simulated results and real data.

Table 4.12 – Measures of fit between data series and simulated results.

Variables	Coefficient of determination (R^2)	MAPE	MAD	RMSE
Freight transport activity	90%	3%	142.8 (10^9 tkm)	63.8 (10^9 tkm)
Total freight emissions	75%	5%	6.7 (10^6 ton)	4.6 (10^6 ton)
Total truck fleet	95%	8%	230,148 un	157,269 un
Truck sales	30%	93%	75,934 un	79,387 un

As can be observed in Table 4.12, the results for freight transport activity, total freight emissions, and total truck fleet presented small error percentages, with a good percentage of R^2, which is considered acceptable for the model. The results of the variable truck sales, however, have not presented a good fit to the real data, which led us to the step of adjusting the model's input parameters, seeking to optimize the simulation results, using the optimization tool of the Vensim® Pro software. Table 4.13 shows the initial values used for each input parameter and the values after model optimization.

The only parameter modified by the optimization was the "yearly freight transport activity change" from 3.43% to -0.32%. Although this value improved the fit of new truck sales, other results such as total truck fleet and emissions got worse. Then, the initial value of the mentioned parameter was kept for the simulation.

Table 4.13 – Initial and optimized input parameters.

Parameters	**Initial values**	**Optimized values**
yearly freight transport activity change	0.0343	-0.0032
tkm/truck	504249	504249
tkm/train	1.03586e+08	1.03586e+08
tkm/barge	1.13787e+08	1.13787e+08
diesel+biodiesel truck efficiency	0.058	0.058
CNG truck efficiency	0.0629	0.0629
electric truck efficiency	1.4	1.4
hydrogen truck efficiency	0.11	0.11
diesel train efficiency	0.0046625	0.0046625
electric train efficiency	53.1	53.1
diesel barge efficiency	0.0038	0.0038
electric barge efficiency	28	28
road diesel $KgCO_2/L$	2.4273	2.4273
road biodiesel $KgCO_2/L$	2.1879	2.1879
road CNG CO_2 emission factor	2.101	2.101
road biomethane CO_2 emission factor	0.24	0.24
rail diesel $KgCO_2/L$	2.4273	2.4273
waterway diesel $KgCO_2/L$	2.4273	2.4273

Regarding the behavior of the new truck sales curve, by inspecting the graph in Figure 4.15, we can see an abrupt drop in truck sales in 2015 and 2016, which can be explained by the economic crisis experienced in Brazil in that period with negative GDP growth, also affecting the automotive sector. It means that external factors that impact this variable are not being considered within the model boundaries, yielding a large error between actual and simulated truck sales. After this period, the simulated curve tends to follow the same behavior as the real truck sales curve. Despite the economic scenario impacting vehicle sales, we decided not to include this factor in the model. We, however, point out that the sale of new vehicles is susceptible to the economic situation of the region or country under study.

4.3.4.7 Sensitivity analysis

Sensitivity analyzes were performed to demonstrate the levels of confidence concerning the model's representation of reality based on the variation of parameters with a certain degree of uncertainty. Thus, one can identify the impact of changing these parameters on the main outputs of the model over time.

According to STERMAN (2000), there are three types of sensitivity: numerical, behavior mode, and policy sensitivity. Numerical sensitivity exists when a change in parameters changes the numerical values of the results. Behavior mode sensitivity exists when a change in parameters changes the patterns of behavior generated by the model (i.e., from smooth adjustment to oscillation or from s-shaped growth to overshoot and collapse). Policy sensitivity exists when a change in assumptions reverses the impacts or desirability of a proposed policy.

Numerical sensitivity is important and the uncertainty in parameter values must be tested. However, for most SD models' purposes, behavior mode sensitivity, and especially policy sensitivity, are more important given that such models are behavior pattern oriented (STERMAN, 2000; HEKIMOĞLU and BARLAS, 2016). We have performed all three types of sensitivity analysis. The input parameters and their range of uncertainty are shown in Table 4.14.

Table 4.14 – Parameters used on the sensitivity analysis test.

Parameters	Average	Min	Max
yearly freight transport activity change %	0.0343	-0.0032	0.0760
tkm/truck	526,848	504,249	556,414
tkm/train	103,585,569	86,330,935	131,011,518
tkm/barge	113,786,560	91,725,945	159,798,150
diesel/biodiesel truck efficiency (l/tkm)	0.0577	0.0272	0.1139
CNG/biomethane truck efficiency (m^3/tkm)	0.0629	0.0297	0.1242
electric truck efficiency (kWh/tkm)	1.4000	1.1200	1.8700
hydrogen truck efficiency (kgH_2/tkm)	0.1100	0.0800	0.1600
diesel train efficiency (l/tkm)	0.0047	0.0029	0.0065
electric train efficiency (Wh/tkm)	53.1000	43.9000	60.0000
diesel barge efficiency (l/tkm)	0.0020	0.0009	0.0038
electric barge efficiency (Wh/tkm)	28.0000	25.2000	30.8000
road diesel emission factor ($kgCO_2$/l)	2.6970	2.4273	2.9667
road biodiesel emission factor ($kgCO_2$/l)	2.4310	2.1879	2.6741
road CNG emission factor (kg CO_2/m^3)	2.1010	1.8909	2.3111
road biomethane emission factor (kg CO_2/m^3)	0.2400	0.216	0.2640
rail diesel emission factor ($kgCO_2$/l)	2.6970	2.4273	2.9667
waterway diesel emission factor ($kgCO_2$/l)	2.6970	2.4273	2.9667

The variation of yearly freight transport activity change considered the minimum and maximum values from 2010 to 2020 (EPE, 2022). The amount of transport service, measured in tkm, performed by truck, train, and barge considered the minimum and maximum values from the historical series of transport activity by mode (EPE, 2022) and the respective truck fleets (SINDIPEÇAS and ABIPEÇAS, 2022) and train and barge fleets (CNT, 2021). The variation of all energy efficiency factors was taken from different sources (MME et al., 2020; EPL and IEMA, 2021; BAZALUK et al., 2021; ĆWIL et al., 2021; FERREIRA, 2022; HYZON, 2022; MERCEDES-BENZ, 2022; VOLVO, 2022). For CO_2 emission factors, we have used the average value and ±10% as a range of uncertainty.

The sensitivity test was performed with the Latin Hypercube Sampling method (200 simulations), which is considered appropriate for SD models (FORD, 2009; KWAKKEL and PRUYT, 2013). In this method, the range of possible values for each parameter is divided into N strata of equal probability. For each input parameter, it selects one value of the N strata on a random basis, which is repeated in all simulations (FORD, 2009). The uncertainties in the parameters are described as uniformly distributed, as we are interested in the diversity of dynamics that can be generated, and not in accurately predicting the probability of these dynamics (KWAKKEL and PRUYT, 2013). The sensitivity simulation is provided by the software Vensim® Pro. The sensitivity graph shows the base case run as a solid blue line. The yellow area shows the 50% confidence bound estimated from the 200 simulations. The same is true for the green area with 75% confidence, the blue area with 95% confidence, and the grey area with 100% confidence. Figure 4.16 presents the sensitivity graph for truck, train, and barge fleets.

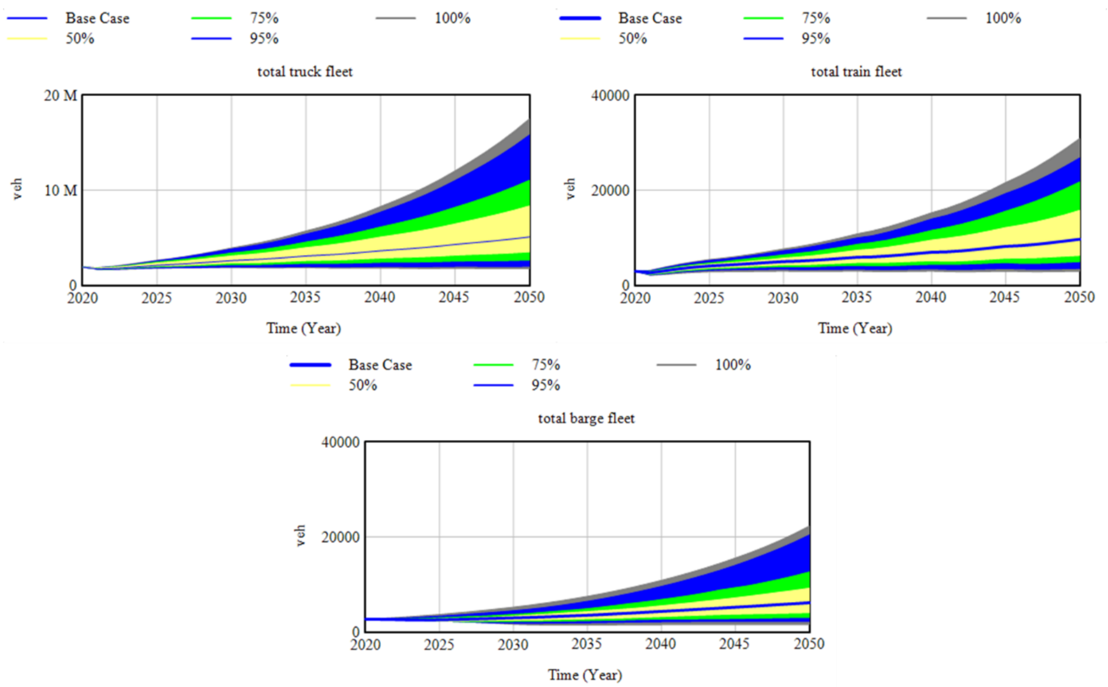


Figure 4.16 – Sensitivity analysis for truck, train, and barge fleets.

The truck fleet uncertainty ranges from 1,7 million to 17,5 million in 2050, while the train and barge fleets range from 2.967 to 30.934 and from 1.560 to 22.327, respectively. These huge variations can be explained by the incidence of two uncertain parameters (transport activity and the level of transport activity performed by vehicle), which both impact the level of the fleets. Moreover, the uncertainty is low in the first decade and tends to increase in the last two decades of simulation, as a consequence of stock accumulations in the long term. Despite the numerical uncertainty, the pattern of behavior is kept through time. Figure 4.17 shows the sensitivity graph for diesel/biodiesel, CNG, electricity, hydrogen, and biomethane consumption from the road transport mode.

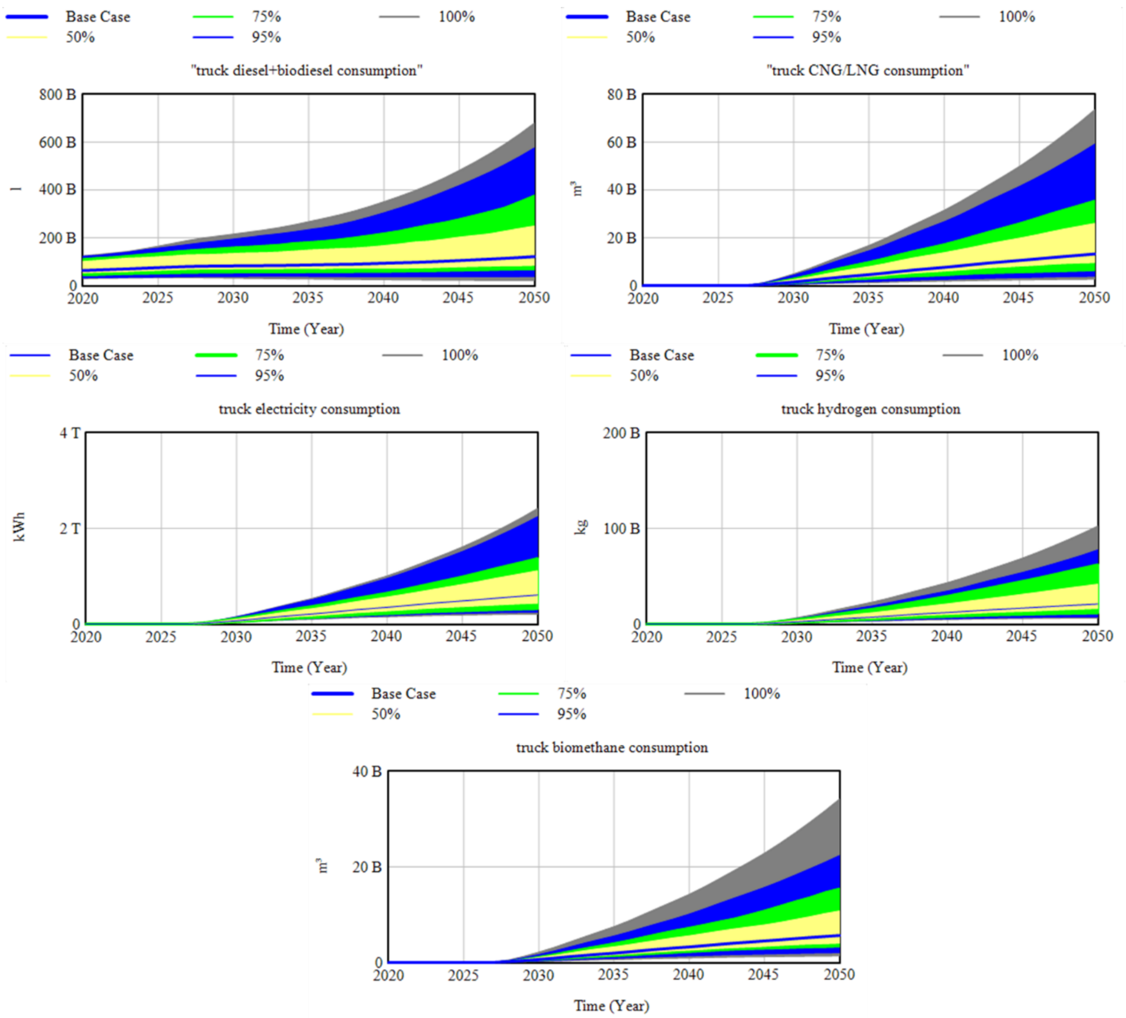


Figure 4.17 – Sensitivity analysis for diesel/biodiesel, CNG, electricity, hydrogen, and biomethane consumption from the road mode.

From the uncertainty bounds, we can say that most of the simulations (out of the 200 simulations) are above the baseline. The consumption of alternative energy sources starts showing significant uncertainty for the scale used after the second half of the first decade, due to the slow introduction of policies towards alternative fuels.

The sensitivity analysis for the rail and waterway modes shows similar behavior to the road mode regarding diesel and electricity consumption, except that electricity consumption for these modes starts to be significant after 2035. Figure 4.18 shows the sensitivity graph for diesel and electricity consumption from the rail and waterway modes.

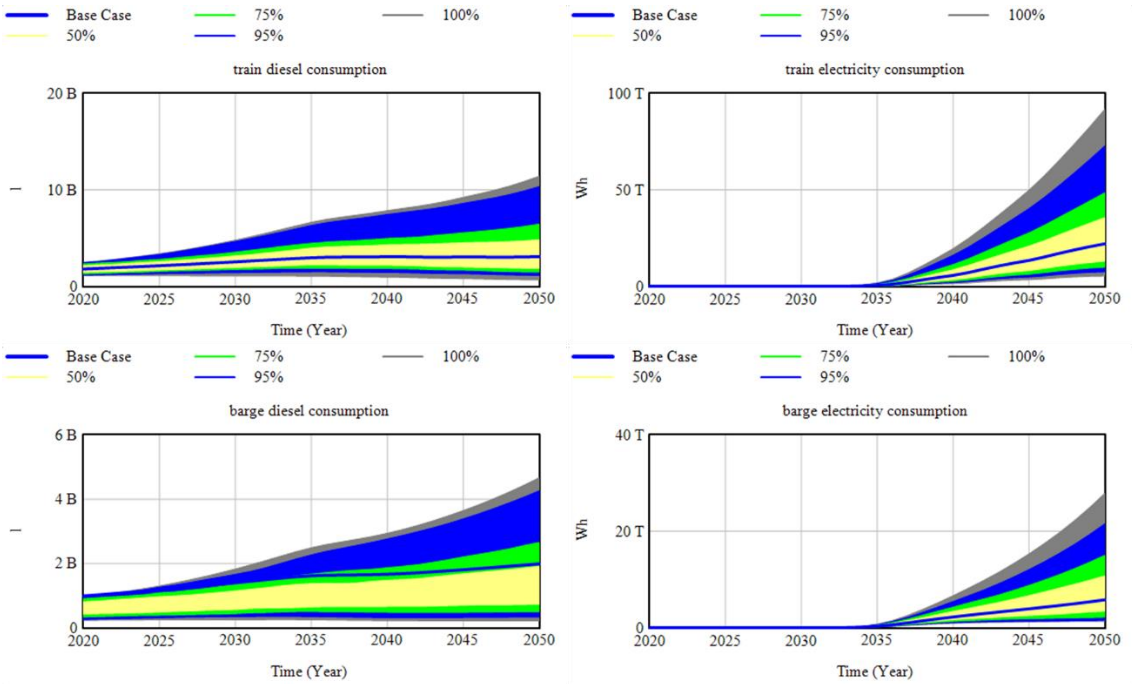


Figure 4.18 – Sensitivity analysis for diesel, and electricity consumption from the rail and waterway modes.

Finally, the sensitivity analysis for CO_2 emissions is represented in Figure 4.19. By the scale, we can note the similarity of total freight emissions and road CO_2 emissions, as the majority of emissions come from this mode. The lower and upper bounds of the uncertainty of total freight emissions range from 2,47 billion to 27,33 billion tons in 2050. Despite the different speeds, all simulations present the same growth behavior.

Although the numerical results present great uncertainties, especially in the long term, the behavior mode sensitivity analysis has revealed that the model is robust, that is, the general pattern of behavior is not altered by changes in the estimates of the parameters.

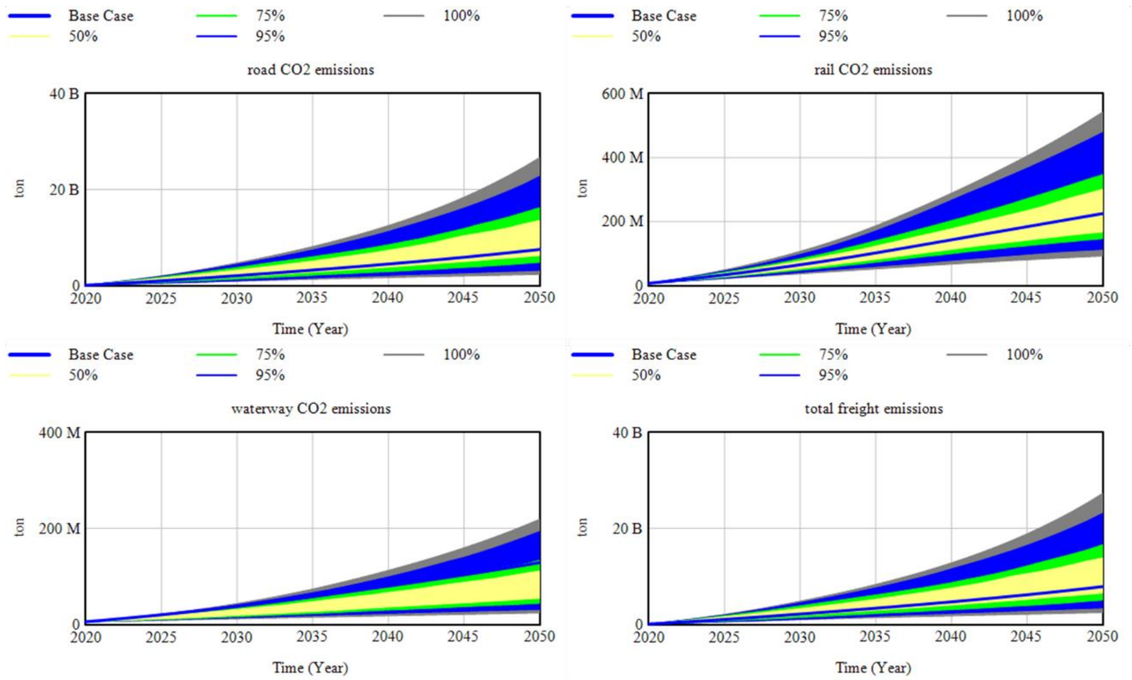


Figure 4.19 – Sensitivity analysis for CO_2 emissions from the road, rail, and waterway modes and total freight CO_2 emissions.

Regarding the policy sensitivity test, we have tested the proposed policies individually under the parameter variations to be able to assess their impacts on the results. The tested policies are: (i) policies towards alternative modes; (ii) policies towards alternative fuels (including the blend of diesel and biodiesel); and (iii) policies towards speeding up fleet renewal. The results are compared with the business-as-usual (BAU) scenario, in which no policy is applied. Unlike the scenarios for simulating the results presented in Section 4.4, in which policies are simulated with fixed input parameters, here we simulate the impact of policies on emissions under varying input parameters within uncertainty bounds. Figure 4.20 shows the policy sensitivity results for the variable "total freight emissions".

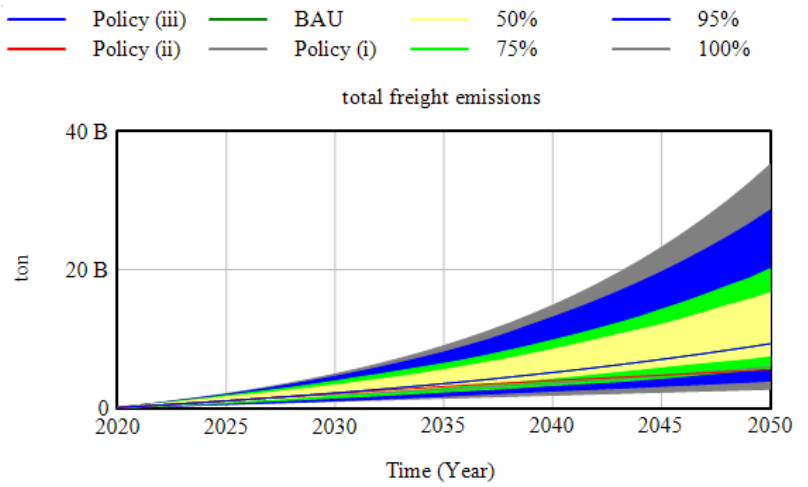


Figure 4.20 – Policy sensitivity analysis for total freight CO_2 emissions.

The lower and upper bounds of total freight emissions uncertainty are 2.73 billion and 35.26 billion tons in 2050. Numerically, this range of uncertainty is higher than when the policies were set unchanged. However, none of the policies caused an undesired impact (increase) on emissions under input parameters variation. The only policy that presented a result equal to the BAU scenario was Policy (iii), which means that individually it does not have an impact on emissions and that, therefore, it should be applied in a complementary way with other policies. Although the results are numerically sensitive to the uncertainty of the parameters, the model showed robustness in the behavior mode and policy sensitivity tests.

4.4 Scenarios setting and results

The scenarios are based on some key model variables related to the decarbonization policies to change the behavior of the freight transport system. Specifically, the model has four policies: (i) policies toward alternative modes; (ii) policies toward alternative fuels; (iii) policies toward increasing the percentage of biodiesel in diesel blend; and (iv) policies toward speeding up fleet renewal. Each policy has a configuration set regarding its implementation goals and deadlines.

Regarding policies towards alternative modes, Brazilian's National Logistics Plan – NLP 2035 (MINISTRY OF INFRASTRUCTURE and EPL, 2021) predicts three different setups of modal share in 2035, each one depending on a set of infrastructure investments in the Brazilian transport network to reduce the roadway share and increase the railway and waterway share. Table 4.15 presents the setups for policies toward alternative modes.

Table 4.15 – Initial modal share and projections for 2035 (%).

Modes	2020	Setup 1	Setup 2	Setup 3
Roadway	63.3	55	40	32
Railway	21.7	31	43	47
Waterway	14.9	13	16	19

Source: EPE (2022); MINISTRY OF INFRASTRUCTURE and EPL (2021).

Concerning the policies toward alternative fuels, Table 4.16 shows two configuration sets (Setups 1 and 2) predicted by BCG and ANFAVEA (2021), regarding the percentage of use of each energy source by trucks in 2035. For railways and waterways, we have considered independent initiatives announced by some concessionaires to be met in 2050. For all modes, Setup 3 was added to assess the impact of a more restricted policy in the longer term (2050).

Table 4.16 – Energy share and projections for 2035 (road) and 2050 (rail and waterways) (%).

Modes	Fuels	2020	Setup 1	Setup 2	Setup 3
Roadway	Diesel/biodiesel	100	86	68	0
	Natural gas/biomethane	0	7	10	50
	Electricity	0	7	15	40
	Hydrogen	0	0	7	10
Railway and waterway	Diesel	100	100	50	0
	Electricity	0	0	50	100

Source: based on BCG and ANFAVEA (2021); VLI (2022); RUMO (2022); VALE (2022).

For policies towards increasing the percentage of biodiesel in diesel blend, Table 4.17 shows two configuration sets, also predicted by BCG and ANFAVEA (2021) for 2035.

Table 4.17 – Biodiesel percentage in diesel blend and projections for 2035.

Fuels	2020	Setup 1	Setup 2
Diesel	88	82	70
Biodiesel	12	18	30

Source: based on BCG and ANFAVEA (2021).

Lastly, the policy towards speeding up fleet renewal was proposed to assess the impact of accelerating the scrappage rate of the old truck fleet. In this case, the only decision is the application of such policy, when, and with which duration. Table 4.18 shows the business-as-usual (BAU) and all the proposed scenarios, each one with a specific combination of the policies' setups and their respective time limit to be met (defined in the RAMP function).

In the BAU scenario, no policy is applied, and the freight transport modal and energy source shares remain the same as in 2020.

Scenarios collection 1, composed of scenarios 1 to 8, aims to evaluate the individual impact of each setup of policies toward alternative modes, policies toward alternative fuels, and policies toward increasing the percentage of biodiesel in diesel blends.

Scenarios collection 2, composed of scenarios 9 to 17, aims to evaluate the impact of all possible combinations between the setups of the policies towards alternative modes, and policies towards alternative fuels.

Scenarios collection 3, composed of scenarios 18 to 26, considered three of the previous scenarios (a conservative, a moderate, and an innovative). For each one of them, we have added setup 2 for policies toward increasing the percentage of biodiesel in diesel blend and varied the time limit of the policy towards speeding up fleet renewal (in which the goal should be met: 2025, 2030, or 2035).

Given the uncertainty of the time frame in which the policies will be met, in scenarios collection 4, composed of scenarios 27 to 32, we also simulated two different limits of time (2025 and 2050) for policies toward alternative modes and policies toward alternative fuels.

Finally, scenarios collection 5, composed of scenarios 33 to 35, evaluates the variation of the results given the uncertainty range of the freight transport demand, considering a steady percentage drop, a steady percentage increase, and a random variation for the percentage of demand oscillation of freight transport.

Table 4.18 – Proposed scenarios for simulation.

Collection of scenarios	Scenarios	Setups of alternative modes	Setups of alternative fuels	Setups of biodiesel use	RAMP alternative modes	RAMP alternative fuels and biodiesel	RAMP speed up the fleet renewal
BAU	BAU	0	0	0	0	0	0
1	Scenario 1	1	0	0	2035	0	0
	Scenario 2	2	0	0	2035	0	0
	Scenario 3	3	0	0	2035	0	0
	Scenario 4	0	1	0	0	2035	0
	Scenario 5	0	2	0	0	2035	0
	Scenario 6	0	3	0	0	2050	0
	Scenario 7	0	0	1	0	2035	0
	Scenario 8	0	0	2	0	2035	0
2	Scenario 9	1	1	0	2035	2035	0
	Scenario 10	1	2	0	2035	2035	0
	Scenario 11	1	3	0	2035	2050	0
	Scenario 12	2	1	0	2035	2035	0
	Scenario 13	2	2	0	2035	2035	0
	Scenario 14	2	3	0	2035	2050	0
	Scenario 15	3	1	0	2035	2035	0
	Scenario 16	3	2	0	2035	2035	0
	Scenario 17	3	3	0	2035	2050	0
3	Scenario 18	1	1	2	2035	2035	2035
	Scenario 19	1	1	2	2035	2035	2030
	Scenario 20	1	1	2	2035	2035	2025
	Scenario 21	2	2	2	2035	2035	2035
	Scenario 22	2	2	2	2035	2035	2030
	Scenario 23	2	2	2	2035	2035	2025
	Scenario 24	3	3	2	2035	2050	2035
	Scenario 25	3	3	2	2035	2050	2030
	Scenario 26	3	3	2	2035	2050	2025
4	Scenario 27	1	1	2	2025	2025	0
	Scenario 28	1	1	2	2050	2050	0
	Scenario 29	2	2	2	2025	2025	0
	Scenario 30	2	2	2	2050	2050	0
	Scenario 31	3	3	2	2025	2025	0
	Scenario 32	3	3	2	2050	2050	0
5	Scenario 33	3	3	2	2035	2050	0
	Scenario 34	3	3	2	2035	2050	0
	Scenario 35	3	3	2	2035	2050	0

For all scenarios, the main numerical output related to total freight emissions is presented in Appendix C.

4.4.1 BAU Scenario

In the BAU scenario, in which no policy is applied to reduce the emissions from the freight transport sector, we present the results regarding the truck fleet size, truck sales, fuel consumption, and emissions. Figure 4.21 presents the total truck fleet and truck sales per year.

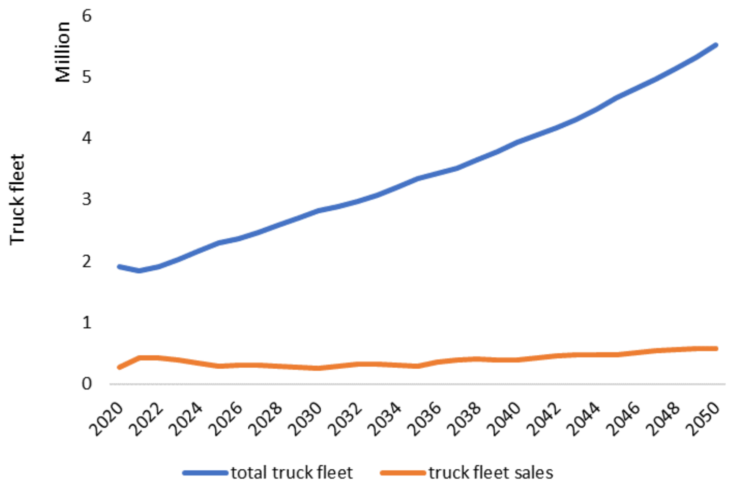
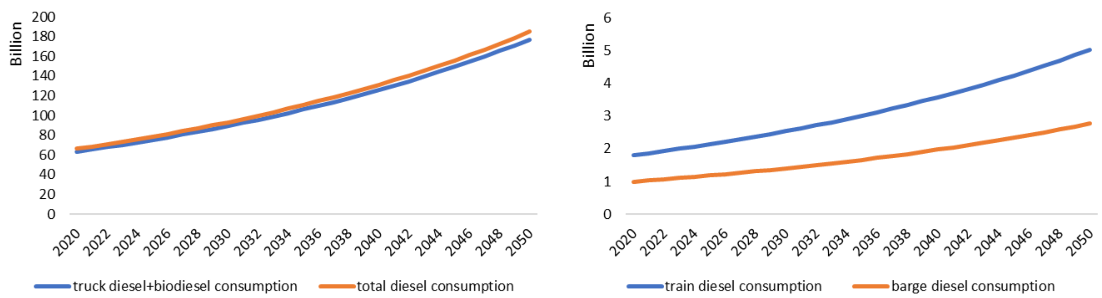


Figure 4.21 – Total truck fleet and truck sales per year.

In this scenario, the total truck fleet will increase from nearly 2 million in 2020 to more than 5.5 million in 2050. The truck sales will range between 250 and 570 thousand units per year to replace the scrapped vehicles and meet the growing demand. However, in this scenario, diesel is the only fuel used for all freight transport modes[4]. Figure 4.22 presents the total diesel consumption and the diesel consumption by mode.



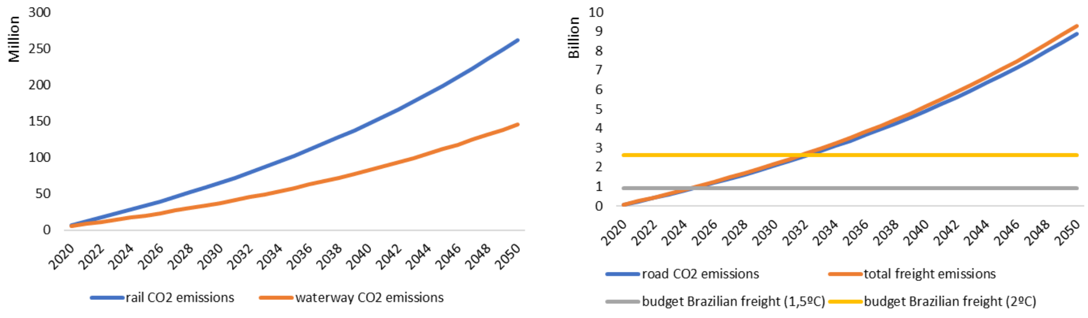
(a) (b)

Figure 4.22 – Diesel consumption from (a) road and all modes and (b) rail and waterways

Diesel consumption will almost triple in 20 years, in which road mode will be responsible for 95%, while rail and waterway modes for 3% and 2% of diesel consumption,

[4] For trucks, we refer to diesel already considering 12% of biodiesel in the blend.

respectively. It will also reflect in the CO_2 emissions of each transport mode. Figure 4.23 shows the emissions from each mode and the total freight emissions.



(a) (b)

Figure 4.23 – CO_2 emissions from (a) rail and waterways, and (b) road and all modes.

As expected, most CO_2 emissions come from the road transport mode, reaching an accumulation of approximately 9 billion tons in 2050. In this case, the estimated emissions budget for the Brazilian freight sector for limiting global warming to 1.5°C or 2°C will be reached in 2025 and 2032, respectively.

4.4.2 Scenarios collection 1

In the first scenarios collection, we assess the individual impact of each one of the different policy setups on freight emissions. Scenarios 1, 2, and 3 are related to the gradual increase in the use of alternative modes (railways and waterways). Scenarios 4, 5, and 6 are related to the gradual increase in the use of alternative fuels (electricity, hydrogen, and natural gas/biomethane). Scenarios 7 and 8 are related to the increase in the percentage of biodiesel in diesel. Figure 4.24 shows the results of the first six scenarios in comparison with the BAU scenario.

Road emissions and total freight emissions present the same behavior, with BAU being the worst scenario. On the other hand, it is interesting to note that Scenarios 2 and 3 (both about decreasing the road share and increasing the alternative modes share) have a better impact on emissions than all the scenarios of policies regarding alternative fuels. This is true at least for the time horizon considered since Scenario 6 aims to eliminate the sale of diesel-powered vehicles (trucks, trains, and barges) by 2050. After this implementation period, Scenario 6 would be the best in terms of reducing CO_2 emissions, despite the remaining diesel-powered vehicles circulating in the market until they are completely scrapped. Rail and waterway emissions, however, would increase under policies promoting these alternative modes of transport, as expected, while policies promoting their electrification would reduce their emissions.

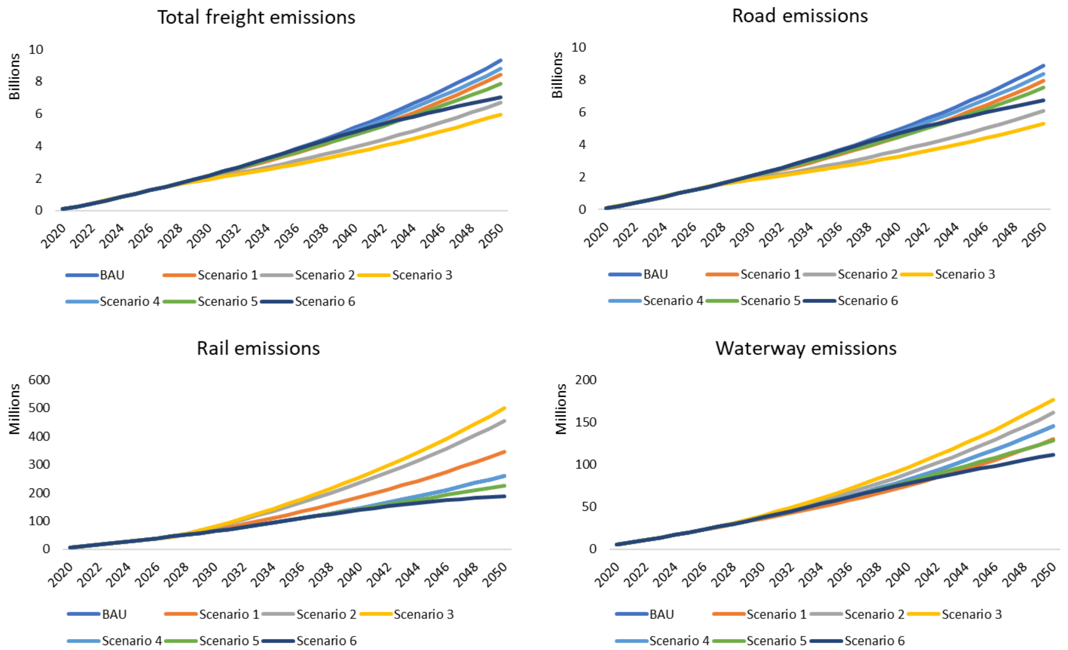


Figure 4.24 – CO_2 emissions in Scenarios 1 to 6 compared to the BAU Scenario.

Regarding Scenarios 7 and 8, we compared the emissions from the road mode under policies towards increasing the percentage of biodiesel in diesel from the current 12% to 18% and 30%, respectively. Figure 4.25 shows that these policies do not have a significant impact on road emissions compared to the BAU scenario. The reduction of accumulated emissions in 2050 would be 0.5% and 1.5% under Scenarios 7 and 8, respectively.

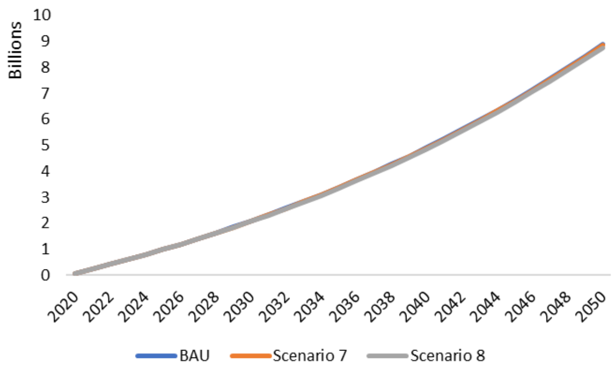


Figure 4.25 – CO_2 emissions in Scenarios 7 and 8 compared to the BAU Scenario.

In all the scenarios, the estimated emissions budget for the Brazilian freight sector for limiting global warming to 1.5°C would be reached in 2025. Regarding the budget for limiting global warming to 2°C, it would be reached in 2035 in the best Scenario 3.

4.4.3 Scenarios collection 2

In the second scenarios collection, we assess the effect of all setup combinations of the policies toward alternative modes and policies towards alternative fuels. Figure 4.26 shows the results of total freight emissions and emissions by mode in comparison with the BAU scenario.

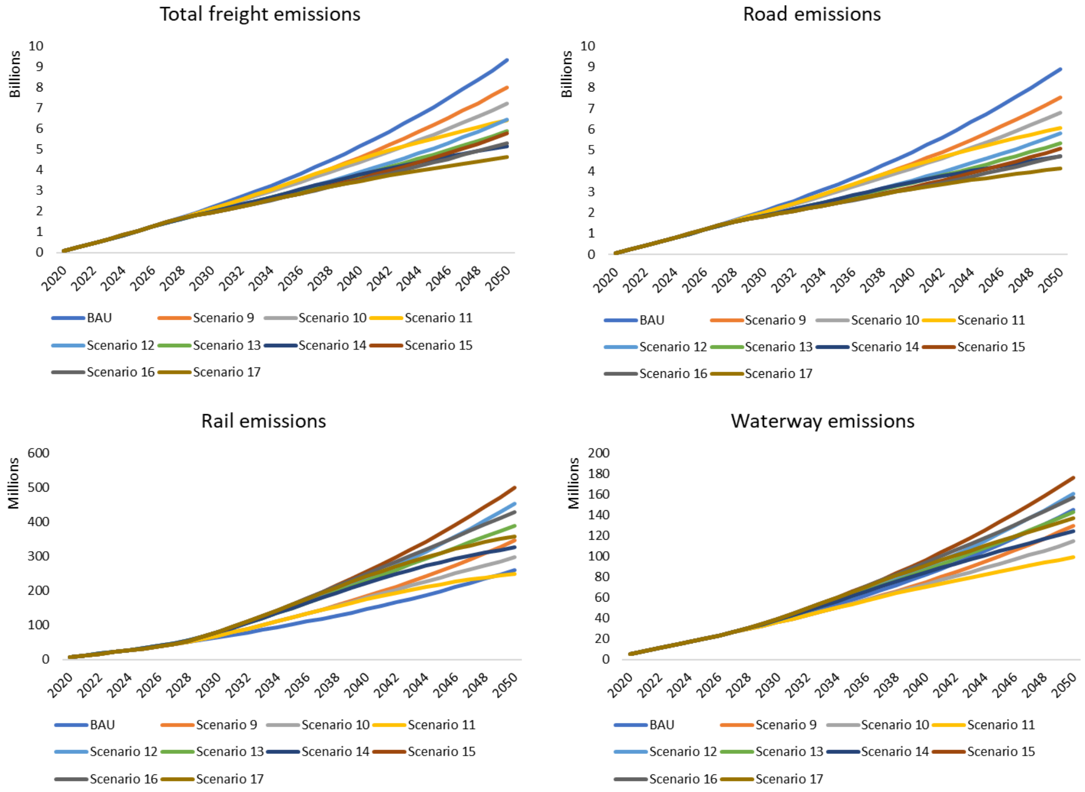


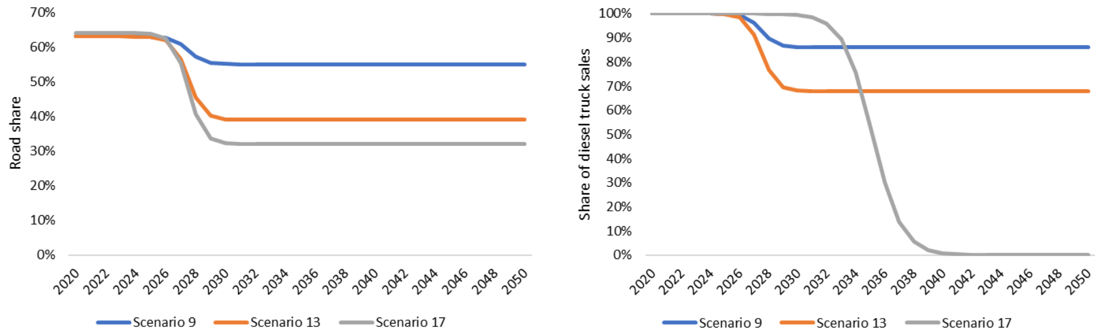
Figure 4.26 – Total freight CO_2 emissions in Scenarios 9 to 17 compared to the BAU Scenario.

Despite rail and waterway emissions increase under the applied policies, in a system-wide perspective, total emissions can decrease by up to 50% in Scenario 17, in which policies aim at a drastic reduction in the use of the road mode, in addition to zeroing out the sales of diesel-powered vehicles by 2050.

In all scenarios, the estimated emissions budget for the Brazilian freight sector for limiting global warming to 1.5°C would be reached in 2025. Regarding the budget for limiting global warming to 2°C, it would be reached in 2035 in the best Scenarios 15, 16, and 17.

4.4.4 Scenarios collection 3

Considering the previous results, we have chosen three perspectives to analyze: a conservative, Scenario 9; a moderate, Scenario 13; and an innovative one, Scenario 17. Figure 4.27 shows the road share and the percentage of diesel-powered truck sales in the chosen scenarios.



(a) (b)

Figure 4.27 – (a)Road share and (b) share of diesel truck sales, in Scenarios 9, 13, and 17.

Road share stabilizes in 2035 at 55%, 39%, and 32% in Scenarios 9, 13, and 17, respectively. Sales of diesel trucks fall progressively and reach 86% in 2035 in Scenario 9, 68% in 2035 in Scenario 13, and 0% around 2040 in Scenario 17. It means that from the conservative perspective, the traditional transport mode and energy source are still in high use for decades ahead. In contrast, in the innovative perspective, the traditional gives more space to alternative transport modes and energy sources, while the moderate perspective is in-between the conservative and innovative cases. It is important to note that some targets of policies are faster to implement, bringing light emissions mitigation, while more ambitious targets might take more time to be implemented, showing better decarbonization results. Policy-makers have to be aware of this trade-off to make decisions aligned with their specific emissions budgets and timeframes.

For each one of the three scenarios, we have added the policies toward speeding up fleet renewal with three different time limits (in which the goal should be met: 2025, 2030, or 2035). The goal of this policy is to accelerate the scrappage rate of old diesel-powered trucks to increase the demand for trucks powered by alternative fuels. Figure 4.28 presents the market share of diesel-powered trucks in all considered scenarios.

In the conservative case, by speeding up the truck scrappage rate, the market share of diesel-powered trucks falls from 86% to 80% in 2050 (comparing Scenarios 18-20 and Scenario 9). In the moderate case, the market share of diesel-powered trucks falls from 69% to 58% (comparing Scenarios 21-23 and Scenario 13), and in the innovative case, it falls from 9% to 1% (comparing Scenarios 24-26 and Scenario 17).

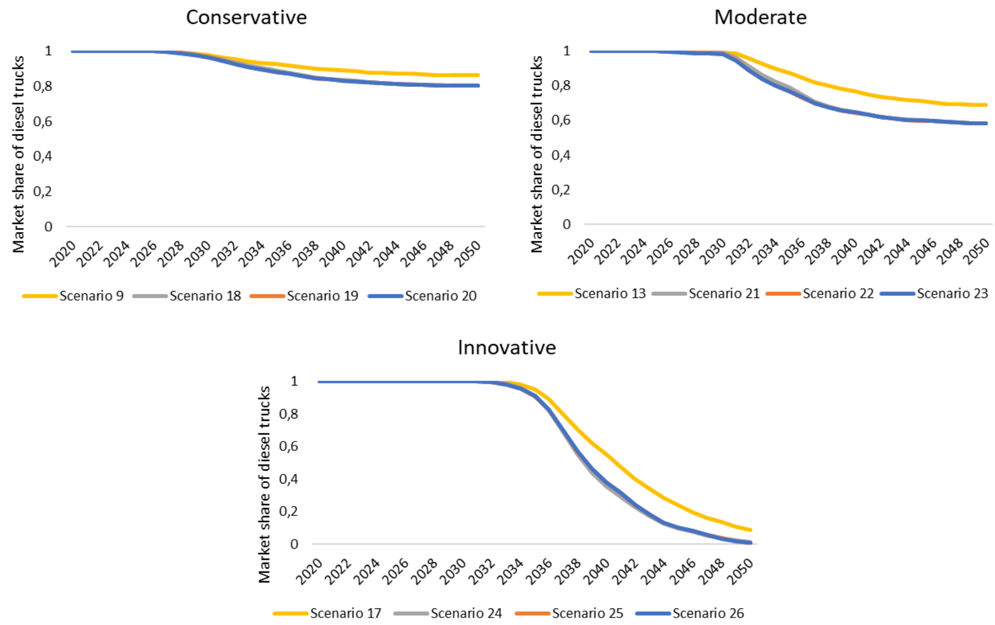


Figure 4.28 – Market share of diesel-powered trucks for a conservative, moderate, and innovative context.

Figure 4.29 presents the total CO_2 emissions for the conservative case in Scenarios 18, 19, and 20, in comparison with the original Scenario 9; the moderate case in Scenarios 21, 22, and 23, in comparison with the original Scenario 13; and the innovative case in Scenarios 24, 25, and 26, in comparison with the original Scenario 17.

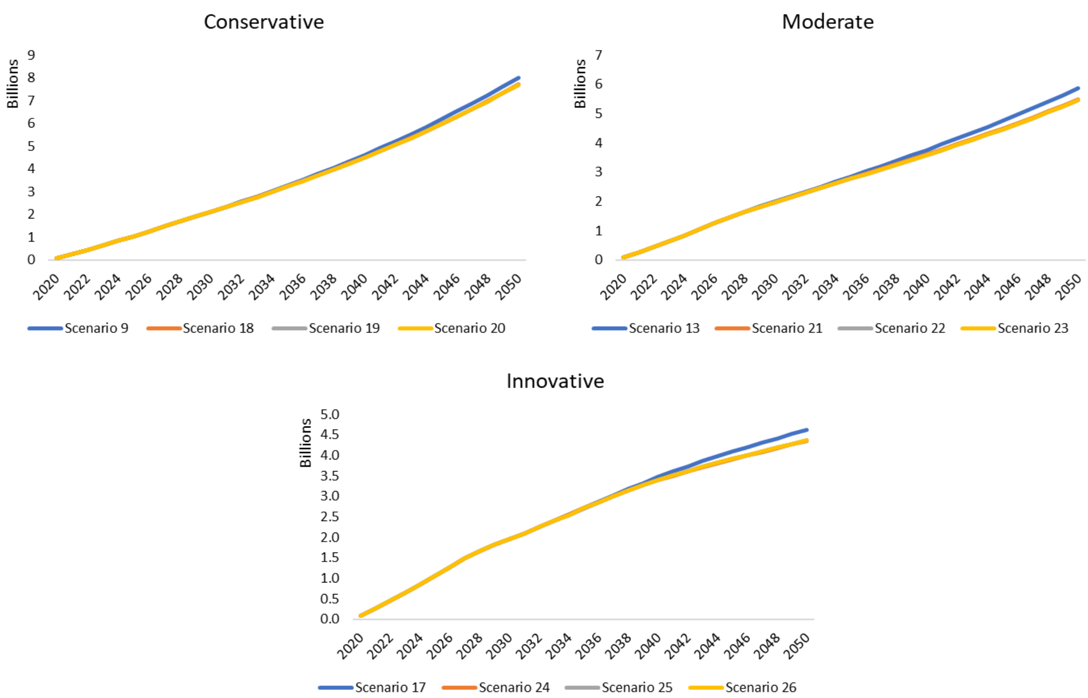


Figure 4.29 – Total freight CO_2 emissions for a conservative, moderate, and innovative context.

Scenarios 18 to 20 show a reduction of approximately 4% in emissions compared to Scenario 9. Scenarios 21 to 23 have a reduction of 7% compared to Scenario 13 and in

Scenarios 24 to 26, the emissions reduction is 6% in comparison to Scenario 17. In other words, the scenarios in which there is an acceleration of truck scrapping present a slight reduction in emissions compared to the scenarios in which there is no such acceleration. However, there is no significant difference in emissions between the scenarios in which scrapping accelerates over 5, 10, or 15 years.

In all the scenarios, the estimated emissions budget for the Brazilian freight sector for limiting global warming to 1.5°C would be reached in 2025. Regarding the budget for limiting global warming to 2°C, it would be reached in 2035 in Scenarios 21 to 26.

4.4.5 Scenarios collection 4

In scenarios collection 4 (Scenarios 27 to 32), we evaluate the time limit for implementing policies regarding alternative modes and alternative fuels, since these are the policies with greater potential for reducing emissions. For each scenario, the simulated deadlines for the established policies' targets to be reached are 2025 and 2050. The results are compared with the scenarios in which policies implementation deadline is 2035 (Scenarios 9, 13, and 17 for a conservative, moderate, and innovative comparison, respectively). Figure 4.30 shows the results for total freight emissions in each case individually, and all together.

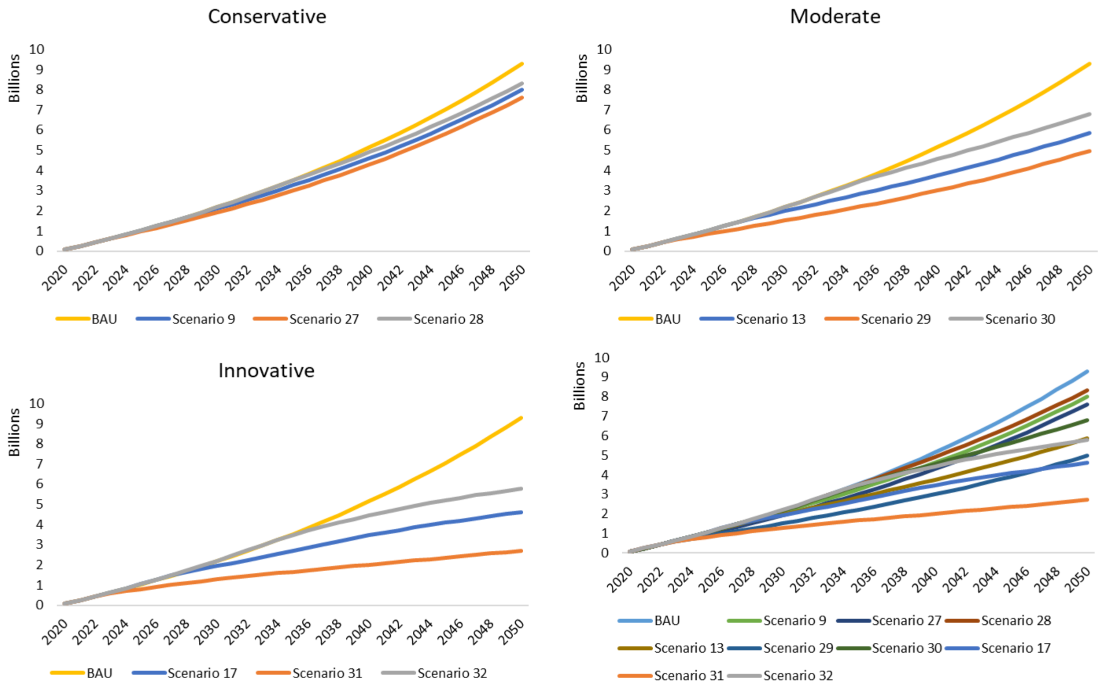


Figure 4.30 – Total freight emissions by varying the time limit of policies regarding alternative modes and fuels.

Table 4.19 shows the percentage of total freight emissions reduction by varying the time range of the policies' implementation.

Table 4.19 – Emissions reduction by policies level and their implementation time range.

Policies level	Scenarios	Policies time range	Emissions reduction (%)
Conservative	Scenario 27	2020-2025	18
	Scenario 9	2020-2035	14
	Scenario 28	2020-2050	10
Moderate	Scenario 29	2020-2025	46
	Scenario 13	2020-2035	37
	Scenario 30	2020-2050	27
Innovative	Scenario 31	2020-2025	71
	Scenario 17	2020-2035	50
	Scenario 32	2020-2050	38

Combining policies toward alternative modes and fuels in a conservative context would reduce freight emissions by 14% if the established targets for market shares of transport modes and alternative fuel vehicle sales are to be met in 2035. In case these policies are advanced or delayed, the emissions reduction varies between 10% and 18%. For the moderate level of policies, freight emissions can decrease between 27% and 46%. In an innovative level of policies, such reduction would be between 38% and 71%.

The estimated emissions budget for the Brazilian freight sector for limiting global warming to 1.5°C would be reached in 2025, except in Scenarios 29 and 31, in which it would be reached in 2026. Regarding the emissions budget for limiting global warming to 2°C, it would be reached in 2049 in the best Scenario 31.

4.4.6 Scenarios collection 5

Finally, considering that the input variable related to the variation in future demand for freight transport is highly relevant and significantly impacts the model results, we simulate three scenarios based on the minimum and maximum values from the historical data series (EPE, 2022): Scenario 33 with a constant decline in freight demand (-0.32%); Scenario 34 considering a steady increase in freight demand (7.6%); and Scenario 35 considering a random variation between the previous limits, with increases and decreases over the next three decades. All scenarios were based on Scenario 26 (with an average freight demand). Figure 4.31 presents the total freight emissions in all cases.

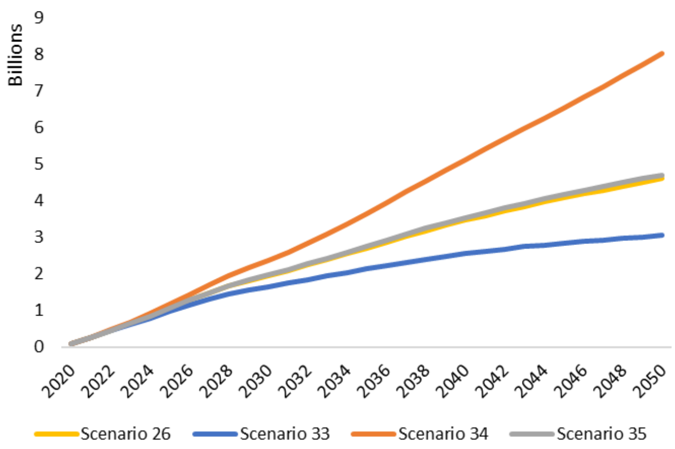


Figure 4.31 – Total freight emissions under freight demand variations.

The accumulated emissions in 2050 in Scenario 35 under the random variation of the demand for freight transport is close to the accumulated emissions under the average demand considered in Scenario 26. Scenario 33 presents 66% and Scenario 34 presents 175% of the accumulated emissions in comparison to Scenario 26 of average demand.

The estimated emissions budget for the Brazilian freight sector for limiting global warming to 1.5°C would be reached in 2025, while the budget for limiting global warming to 2°C would be reached in 2042 in the best Scenario 33.

4.5 Discussions

Based on the results of Scenarios collection 1 (Scenarios 1 to 8), which simulates the individual impact of policies toward alternative modes, policies toward alternative fuels, and policies toward increasing the percentage of biodiesel in diesel blend, it is evident that policy incentives are required in the country to obtain a higher decarbonization result. When compared against the BAU (where no policy incentive is applied), all policies (irrespective of the differences between specific scenario runs) turn out with a lower rate of total emissions from the freight transport system. More specifically, Scenario 3 obtains a 36% emissions reduction in comparison to the BAU scenario, the highest of all three policies. Still, even the least successful scenario in this collection (Scenario 7) obtains a 0.5% reduction, when compared to the BAU scenario. In practical terms, Scenario 3 means to change the modal share and reduce the percentage of use of the road mode from 63% to 32% in 15 years. Railways and waterways would have to increase their shares from 22% to 47% and from 15% to 19%, respectively, which depend on a set of aggressive infrastructure investments in strategic railway and waterway sections in addition to supporting logistics infrastructure (MINISTRY OF INFRASTRUCTURE and

EPL, 2021). In addition, our results show the lagged response of emissions mitigation to incentive policies. All scenarios show little difference from each other in the short to mid-term (until 2030 approximately) and only begin to show differences from 2030 onwards. In other words, nearsighted policymaking may hinder the policies' benefits in the long term if implementation delays are not taken into account.

Afterward, we developed Scenarios collection 2 (Scenarios 9 to 17) by combining policies toward alternative modes and alternative fuels. The rationale behind these scenarios is that, usually, more than one policy is active at the same time. Depending on the policy combination, our results suggested lower emissions from the freight system than when the policies were implemented separately. The best scenario in this collection (Scenario 17) achieved a 50% emissions reduction in comparison to the BAU scenario, while the worst (Scenario 9) achieved a 14% of emissions decrease. It is worth noting that the second set of experiments allows us to measure and assess the compounded effect of simultaneous policies on the freight decarbonization potential and therefore, offer a more realistic set of scenarios to forecast the possible emissions drop.

Then, Scenarios collection 3 (Scenarios 18 to 26) aimed to assess the impact of policies toward speeding up the fleet renewal process by accelerating the scrappage rate of old diesel-powered trucks. The scenarios in which there is an acceleration of truck scrapping modify the market share between vehicles powered by different energy sources and a slight reduction in emissions compared to the scenarios in which there is no such acceleration. From a policymaking perspective, the composite policy set investigated herein offers novel insights into the effects of policy timing to obtain the best possible outcomes in the long term. For instance, the activation and deactivation of the aforementioned policies could be sequenced for longer timeframes until there are diesel-powered trucks in the fleet, working as an extra incentive for some agents such as the investors of alternative energy sources for the automotive sector.

Scenarios collection 4 (Scenarios 27 to 32) was run based on the uncertainty of the time needed to implement and reach each policy's established goals. Considering the policies toward alternative modes and fuels, we have simulated three timeframes of 5, 15, and 30 years for a set of scenarios in conservative, moderate, and innovative contexts. The rationale behind this fourth experiment is that the most effective results come by implementing the policies as fast as possible. In all cases, the faster policies are implemented, the more significant the improvements in terms of emissions drop.

Naturally, it means a highly aggressive effort to implement and achieve ambitious targets in the short term, including radical changes in energy, technology, and infrastructure systems, which feasibility or cost-benefit should be better analyzed.

Scenarios collection 5 (Scenarios 33 to 35) shows how the uncertain range of freight demand can impact the emissions results. Taking the minimum and maximum limits from the historical series (EPE, 2022) of freight transport demand, total freight emissions almost tripled in a period of 30 years. This means that the input variable related to freight demand variation could be better modeled from a macroeconomic perspective in future research.

From the results and discussions presented, it is clear and urgent the need for coordinated cooperation and broad participation of the government and other stakeholders capable of sustaining, encouraging, and enabling innovative scenarios that bring compelling results for the freight transport decarbonization in Brazil. All the policies presented are important to a greater or lesser extent on the path to decarbonization. Naturally, some policies are easier and faster to implement than others (increasing the percentage of biodiesel in the diesel blend and speeding up the fleet renewal process take less effort and investment than changing the fleet technologies and the modal split). The joint implementation of such policies brings greater benefits in a shorter time and becomes important due to joint efforts to balance the effect of increased demand for freight transport in the coming years, despite the intrinsic delays in their implementations. As mentioned in the qualitative research section, the individual effort of a system stakeholder, such as the interviewed freight forwarders, is neither sufficient nor capable of achieving the necessary goals. It takes a joint effort from various sectors so that the change in the system occurs on a large scale and, consequently, the results of decarbonization are enhanced and achieved within the desired timeframes.

On the other hand, it is worth highlighting that the budget estimated for the sector's emissions, suggested in this work due to the absence of official targets, is very superficial and should be analyzed with caution. Firstly, the estimate is based on the percentage of sector emissions in 2020 compared to global emissions, which is expected to change over the next few years. Secondly, this percentage of emissions should not necessarily guarantee or impose the same percentage of the global budget for future freight emissions. It is necessary to consider a fairer balance between countries that have historically developed and polluted more and countries that are still developing and that tend to suffer more from the consequences of global warming. However, the proposal of a specific target to reduce sectoral emissions of Brazilian freight transport is outside the scope of this work, being suggested as a topic for future research. Despite this limitation to analyzing the emissions budgets of the Brazilian freight sector, which should not be as restricted as those of developed countries, the results corroborate the urgency for more forceful actions to promote decarbonization. In all scenarios, the sector budget to limit global warming to 1.5°C would be reached in 2025, while the budget to limit global warming to 2°C would be reached in 2032 in the BAU scenario; in 2035 in the Scenarios collection 1, 2 and 3; in 2042 in Scenarios collection 5; and in 2049 in Scenarios collection 4. Such results indicate that limiting global warming to 1.5°C or 2ºC until 2100 as defined in the Paris Agreement is beyond reach. Despite being a limited uni-sectoral analysis, the results show how close we are to reach the limits defined for global warming. In fact, we do not have more time to delay the necessary actions and spare efforts to face such a great challenge with the serious and collaborative engagement of stakeholders.

Of course, the unavoidable assumptions made in our model regarding the timeframes of policy implementation have a big role in the presented results. For example, if the fleet renewal process takes 15 years as simulated in the basic scenarios, or if it ranges between 5 and 30 years as simulated in the later scenarios, will impact the time in which the emissions budgets will be reached. However, the real-time for fleet renewal process to occur on a large scale is still uncertain. As discussed in the qualitative research section, the time for freight carrier companies to acquire alternative fuel vehicles can reach two years if their conditions are favorable. For example, highly capitalized companies do not depend on the collaboration of other sectors, although the last is considered imperative for the introduction of new technologies on a large scale in the market, reducing their adoption times by small companies and autonomous drivers. However, uncertainty remains about the time frame for the involvement of other sectors, such as infrastructure, regulation, and energy.

Given the research gap found in the literature about SD models that do not present their data or assumptions regarding the delays for policies or improvement actions implementation (GHISOLFI et al, 2022a), our model still makes a contribution to the literature and policymaking by clearly presenting and giving an orientation of how important theses implementation times are for achieving better results.

From the government perspective, our model helps by showing the potential of emissions mitigation results considering the combined effect of multiple decarbonization policies. As already mentioned, priority should be given to policies towards promoting alternative energy sources, especially green or clean energy sources, since they are the only pathway to deep freight decarbonization. Other measures, however, are also important to mitigate the emissions in the meantime, given that the total fleet replacement is not fast, but takes a considerable time, as shown by our model. Even after the sale of fossil fuel vehicles is banned, we may deal with an old fleet running in the market for a long time if the acceleration of scrappage of the old fleet does not take place. Despite the timeframe for policy implementation and emissions budget assumptions, which are subject to improvements, our model supports policymaking in the freight transport sector by presenting emissions mitigation results over time. It is important to assist decisions in a sector with a limited emissions budget and a short deadline imposed by the urgency of global climate actions and the engagement of all countries and sectors.

4.6 Final remarks of the chapter

In this study, we developed an SD model and conducted several simulation experiments to investigate the impact of four policies in the long-term freight transport decarbonization in Brazil: 1) policies toward alternative modes; 2) policies toward alternative energy sources; 3) policies toward increasing the percentage of biodiesel in diesel blend; and 4) policies toward speeding up the fleet renewal process.

The simulation results showed that no single measure can bring a significant reduction in freight transport emissions. Instead, a set of policies is needed to achieve a compelling decarbonization result. Moreover, the sooner the policies are enforced, the better the emissions abatement in the long run. Besides, it is important to take the delays of policies' implementation carefully, since nearsighted policymaking may hinder their benefits in the long term.

Certainly, several economic, social, and technological conditions are unknown in the long term and, therefore, this simulation exercise should be taken with caution. For example, a new technological paradigm and better solutions can emerge within the simulated timeframe, which should be continuously reviewed and updated. Rather than offering a precise forecast of emissions reduction, its essence is to offer a perspective of the need to reinforce policies in the forthcoming years and decades if we are willing to decarbonize the freight transport system. Our model proves useful to test the performance and offers insights to inform policymakers about the expected outcomes of policy interventions – from a complex systems perspective, in line with current debates and challenges within environmental and freight transport-related policymaking.

Scientifically, our model contributes by starting to closing the literature gaps reported by GHISOLFI et al. (2022a) regarding a simulation model with multiple freight decarbonization policy measures in a system-wide perspective and deepening the knowledge about the temporal factors that govern the dynamics of the system's responses to policies implementation, even by highlighting the real data or the unavoidable assumptions in a clear and reproducible model.

Even though our model offers a comprehensive perspective of freight decarbonization policies, there are many possibilities for future research. Besides the policies' targets and timeframes explored, future research could address how the considered policies will be implemented, i.e., investing in the generation and distribution of alternative energy to meet the increasing power demand, investing in vehicle' technologies development in the national market, providing tax and fee exemptions, subsidies, promoting the expansion of refueling/recharging facilities, or investing in electric road systems such as overhead lines (pantographs) and conductive/inductive ground-level power supply, imposing higher taxes on fossil fuels, etc. Regarding alternative transport modes, it could be not only by infrastructure investment but also by imposing barriers or financial levers to discourage or promote different modes of transport. This could integrate a choice modeling approach from the freight forwarders' perspective to better investigate the most influencing parameters of their choice decisions regarding the adoption of alternative fuel vehicles and transport modes.

Moreover, the model could be expanded and other policies added, such as those related to the improvement of vehicles' energy efficiency and vehicle use (how much transport activity a vehicle performs per year), taken in this study as input variables. Another input that deserves more attention is the freight transport demand and the factors that influence its variation, especially considering the future market trends. It is very important to better understand the dynamics of the freight demand given its high influence on the rest of the system. Variables related to population, economic development, market factors, and patterns of consumption play a role in such dynamics to be modeled. Another pertinent approach to enrich the proposed model could be the life cycle analysis (well-to-wheel) of the energy sources considered, in contrast to the tank-to-wheel analysis of this study, showing how clean alternative energies are for each case study.

Also, several assumptions were made to build the SD model, i.e., the homogeneity of vehicles without distinction of types, sizes, and other technical specificities that influence transport activity per year and fuel consumption. However, it is important to highlight they can be modified and updated as more data becomes available, depending on the desired level of detail and accuracy. Although the assumptions regarding the time limits for policy targets to be met were based on predictions from government technical reports, consultancy groups, and empirical research in the transport sector, they remain highly uncertain, needing to be continuously monitored and updated according to the real agents' engagement. Future empirical research could be carried out with the energy generation and distribution sector, investors of infrastructure, governmental policymakers, and consumers to raise better knowledge of the impact of their decisions on freight system dynamics.

Other empirical research on the freight transport system can be carried out about its rebound effects. For example, the vehicle's fleet is a limited stock to meet a given freight transport demand, which means that for new green technologies to enter the market sooner, old fleets must be scrapped faster. More research is needed about the factors that can boost this dynamic of vehicle replacement, but also how we should deal with a large amount of scrap resulting from this process. It is important to bear in mind the responsibility of reusing and recycling, reintroducing materials from the old fleet into the supply chain, in addition to planning the environmental future of new fleets with the recycling of batteries and their scarce elements.

Finally, the model can be applied to any region or country by collecting all the necessary data and by adapting the model to their specific target decarbonization policies. Of course, it would require an analysis of the specific context to be modeled. The model can be adapted with different variables since new decarbonization policies can emerge from a different reality. The Group Model Building, a workshop method with multiple system-related agents can help with the conceptual modeling process to identify the important factors to be kept and/or changed in the model.

5 Conclusions

This work analyzed the dynamics of the freight transport system toward decarbonization through a systematic literature review, the development of a conceptual model composed of causal loop diagrams, and the development and application of a System Dynamics model.

The systematic literature review aimed to answer the first research question: *What are the gaps in the dynamics of freight transport decarbonization research?* The literature review of SD models of freight transport decarbonization pointed to a research gap regarding the effort to model the freight decarbonization measures in a system-wide perspective, to explore the understanding of the dynamics of the feedback loops that exist within the system, to analyze whether, how, and when a certain level of emissions reduction can be achieved. Moreover, the time-related factors such as delay assumptions are not clear in the models' descriptions, equations, and diagrams for each decision. The study concludes that this is a major problem because time is crucial for assessing whether simulated policy measures effectively achieve decarbonization targets in the short, medium, and long term and that time lags should be taken into account, in an empirically rigorous way, for freight transport decarbonization models to predict dynamics well.

In the next step of the research, a conceptual model of causal loop diagrams was developed to answer the second research question: *How can we conceptually model the dynamics of the freight transport system to decarbonization measures?* The model linked five decarbonization measures as sub-models raising feedback loops between their main components and showing how these measures affect each other in a reinforcing or balancing way, bringing a more comprehensive view of the system. Moreover, the model pointed out the dynamic levers as policies to promote or stimulate decarbonization, which should be the focus of policymakers to change the status of the system. The identified feedback loops are also dynamic levers that show how the whole system is connected, showing policymakers the possible side effects of their policies that could defeat the desired results. This qualitative analysis contributes to the literature with insights into the dynamics of the implementation of decarbonization strategies that can delay or speed up the system's change over time due to the behavior of exponential growth or balancing feedback loops.

Then, we developed an SD quantitative model to address the third research question: How can we quantitatively model the multiple dynamics of the freight transport decarbonization system? By simulating the dynamics of four different policies, the proposed model is a useful tool for policymakers to gain insights into the expected emissions mitigation results under policy interventions. The more policies are combined and the faster they are implemented, the better the emissions abatement in the long run. Despite the assumptions made, this quantitative model contributes to the literature by integrating different decarbonization measures and highlighting the important temporal factors related to their implementation.

Despite the thesis reaching its proposed objective, many literature gaps identified in Chapter 2 were not addressed, being left for future research. For example, the rebound effect of transport efficiency on logistics costs and, consequently, on freight demand, was not considered in our model. In fact, the dynamics of all decarbonization strategies regarding managing or reducing freight transport demand, improving vehicle utilization, and increasing energy efficiency were left out of our modeling approach. It means that the literature gap about the limited boundaries of freight decarbonization SD models was just partially filled with our quantitative model that addressed policies for shifting freight to low-carbon intensity modes and promoting alternative energy sources. Regarding the addressed decarbonization strategies, our model analyzed them from a macro perspective view to simulate their general implementation times and impacts on emissions mitigation. More detailed and empirical studies can enrich the analysis by considering, for example, all the associated costs and times for each step of the mode choice process, fuel-vehicle choice decisions, and companies' adaptation.

5.1 Further research

The assumptions made concerning important policy dynamics should be approached by future research. This can be done by enriching the proposed SD model with studies of specific policies or decisions, or by modeling them independently with system dynamics models, time series models, or agent-based models. Based on such empirically validated models, the task of integration into large system dynamics models could be undertaken in future research.

As an example, the decarbonization policy regarding reducing freight transport demand should be better investigated in quantitative analysis, due to its huge impact on the whole system. The dynamics of the market demand in response to product prices or logistic costs should be further analyzed, as well as other demand management instruments such as logistics collaborations, partnerships, and vertical integration. The economic development in globalized markets also changes the patterns of consumption and increases e-commerce, which should be closely monitored for proper management of environmental effects.

Unlike the assumption of the proposed quantitative model, the utilization of the vehicle's capacity and other logistics assets can be optimized. The reaction of different companies' levels to emissions mitigation and other policies and how it impacts the use of their fleets should be further investigated. Inventory costs and management should be taken into account, as they affect the dynamics of logistics operations. Marketing strategies and the green image of companies also play a role in this policy measure. Moreover, the energy efficiency of different vehicle technologies is subject to improvements and new research should take it into account.

Considering the policies analyzed in our quantitative model, future research should detail how they could be implemented, besides their targets and time limits. A choice modeling approach could assist by providing insights related to the most influencing parameters of stakeholders' choice decisions regarding the adoption of alternative fuel vehicles and transport modes. Still, the temporal factor should be continuously analyzed in future studies, as this is an imperative factor to predict the decarbonization dynamics of the freight transport system.

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A. Appendix A – Model equations

This appendix presents all the equations and their respective units from the proposed system dynamics model developed in Chapter 4.

(001) "% biodiesel in diesel"= 0*TANH (15*policies towards trucks alternative fuels +0)+0.12 - Units: Dmnl

(002) "% Brazilian freight emissions"= Brazilian freight transport emissions 2020/global CO2 emissions 2020 - Units: Dmnl

(003) "% budget 1.5° C Brazilian freight"= "CO2 budget 1.5ºC"*"% Brazilian freight emissions" - Units: ton

(004) "% budget 2° C Brazilian freight"= CO2 budget 2ºC*"% Brazilian freight emissions" - Units: ton

(005) "% CNG/biomethane truck"= "CNG/biomethane truck fleet"/total truck fleet - Units: Dmnl

(006) "% diesel+biodiesel barge"= ("diesel+biodiesel barge fleet"+old barge fleet)/total barge fleet - Units: Dmnl

(007) "% diesel+biodiesel train"= ("diesel+biodiesel train fleet"+total old train fleet)/total train fleet - Units: Dmnl

(008) "% diesel+biodiesel truck"= ("diesel+biodiesel truck fleet"+total old truck fleet)/total truck fleet - Units: Dmnl

(009) "% electric barge"= electric barge fleet/total barge fleet - Units: Dmnl

(010) "% electric train"= electric train fleet/total train fleet - Units: Dmnl

(011) "% electric truck"= electric truck fleet/total truck fleet - Units: Dmnl

(012) "% hydrogen truck"= hydrogen truck fleet/total truck fleet - Units: Dmnl

(013) average barge age= Time-2005 - Units: Year

(014) "average train age 1960-1969"= Time-1964 - Units: Year

(015) "average train age 1970-1979"= Time-1974 - Units: Year

(016) "average train age 1980-1989"= Time-1984 - Units: Year

(017) "average train age 1990-1999"= Time-1994 - Units: Year

(018) "average train age 2000-2009"= Time-2004 - Units: Year

(019) "average train age 2010-2019"= Time-2004 - Units: Year

(020) "average train age >1959"= Time-1954 - Units: Year

(021) "average truck age 1978-1983"= Time-1983 - Units: Year

(022) "average truck age 1984-1989"= Time-1989 - Units: Year

(023) "average truck age 1990-1995"= Time-1995 - Units: Year

(024) "average truck age 1996-2001"= Time-2001 - Units: Year

(025) "average truck age 2002-2007"= Time-2007 - Units: Year

(026) "average truck age 2008-2013"= Time-2013 - Units: Year

(027) "average truck age 2014-2019"= Time-2019 - Units: Year

(028) barge diesel consumption= transport performed with diesel barge*diesel barge efficiency Units: l

(029) barge electricity consumption= transport performed with electric barge*electric barge efficiency Units: Wh

(030) barge fleet from 2020 onwards= INTEG (barge fleet inflow, 0) Units: veh

(031) barge fleet inflow= IF THEN ELSE (total barge fleet<ideal barge fleet, (ideal barge fleet-total barge fleet)/year, 0) Units: veh/Year

(032) "barge scrappage rate 0-5"= 1-(1+EXP (0.2037*3-6.9993))^-0.8679 Units: Dmnl

(033) "barge scrappage rate 11-15"= 1-(1+EXP (0.2037*13-6.9993))^-0.8679 Units: Dmnl

(034) "barge scrappage rate 16-20"= 1-(1+EXP (0.2037*18-6.9993))^-0.8679 Units: Dmnl

(035) "barge scrappage rate 21-25"= 1-(1+EXP (0.2037*23-6.9993))^-0.8679 Units: Dmnl

(036) "barge scrappage rate 26-30"= 1-(1+EXP (0.2037*28-6.9993))^-0.8679 Units: Dmnl

(037) "barge scrappage rate 6-10"= 1-(1+EXP (0.2037*8-6.9993))^-0.8679 Units: Dmnl

(038) barges scrappage rate= 1-(1+EXP (0.2037*(average barge age/year)-6.9993))^-0.8679 Units: Dmnl

(039) biodiesel barge adoption= barge fleet inflow*"diesel+biodiesel barge share" Units: veh/Year

(040) biodiesel trains adoption= train fleet inflow*"diesel+biodiesel train share" Units: veh/Year

(041) biodiesel trucks adoption= truck fleet inflow*"diesel+biodiesel truck share" Units: veh/Year

(042) biomethane truck efficiency= 0.0629 Units: m^3/(ton*km)

(043) CNG 10 to 11= DELAY FIXED (CNG 5 to 6-"scrappage CNG 6-10", 5, 0) Units: veh/Year

(044) CNG 15 to 16= DELAY FIXED (CNG 10 to 11-"scrappage CNG 11-15", 5, 0) Units: veh/Year

(045) CNG 20 to 21= DELAY FIXED (CNG 15 to 16-"scrappage CNG 16-20", 5, 0) Units: veh/Year

(046) CNG 25 to 26= DELAY FIXED (CNG 20 to 21-"scrappage CNG 21-25", 5, 0) Units: veh/Year

(047) CNG 5 to 6= DELAY FIXED ("CNG/biomethane trucks adoption"-"scrappage CNG 0-5", 5, 0) Units: veh/Year

(048) "CNG TF 0-5 years old"= INTEG ("CNG/biomethane trucks adoption"-CNG 5 to 6-"scrappage CNG 0-5", 0) Units: veh

(049) "CNG TF 11-15 years old"= INTEG (CNG 10 to 11-CNG 15 to 16-"scrappage CNG 11-15", 0) Units: veh

(050) "CNG TF 16-20 years old"= INTEG (CNG 15 to 16-CNG 20 to 21-"scrappage CNG 16-20", 0) Units: veh

(051) "CNG TF 21-25 years old"= INTEG (CNG 20 to 21-CNG 25 to 26-"scrappage CNG 21-25", 0) Units: veh

(052) "CNG TF 26-30 years old"= INTEG (CNG 25 to 26-final scrappage CNG-"scrappage CNG 26-30", 0) Units: veh

(053) "CNG TF 6-10 years old"= INTEG (CNG 5 to 6-CNG 10 to 11-"scrappage CNG 6-10", 0) Units: veh

(054) "CNG truck efficiency"= 0.0629 Units: m³/(ton*km)

(055) "CNG/biomethane truck fleet"= "CNG TF 0-5 years old"+"CNG TF 6-10 years old"+"CNG TF 11-15 years old"+"CNG TF 16-20 years old" +"CNG TF 21-25 years old"+"CNG TF 26-30 years old" Units: veh

(056) "CNG/biomethane truck share"= 0*TANH (15*policies towards trucks alternative fuels+0) + 0 Units: Dmnl

(057) "CNG/biomethane trucks adoption"= truck fleet inflow*"CNG/biomethane truck share" Units: veh/Year

(058) CO2 budget 2ºC= 1.15e+12 Units: ton

(059) control 2°C= IF THEN ELSE (total freight emissions<"% budget 2° C Brazilian freight", 0, 1) Units: Dmnl

(060) DB 10 to 11= DELAY FIXED (DB 5 to 6-"scrappage DB 6-10", 5, 0) Units: veh/Year

(061) DB 15 to 16= DELAY FIXED (DB 10 to 11-"scrappage DB 11-15", 5, 0) Units: veh/Year

(062) DB 20 to 21= DELAY FIXED (DB 15 to 16-"scrappage DB 16-20", 5, 0) Units: veh/Year

(063) DB 25 to 26= DELAY FIXED (DB 20 to 21-"scrappage DB 21-25", 5, 0) Units: veh/Year

(064) DB 5 to 6= DELAY FIXED (biodiesel trucks adoption-"scrappage DB 0-5", 5, 0) Units: veh/Year

(065) "DBBF 0-5 years old"= INTEG (biodiesel barge adoption-DBBF 5 to 6-"scrappage DBBF 0-5", 0) Units: veh

(066) "diesel+biodiesel TF 26-30 years old"= INTEG (DB 25 to 26-final scrappage DB-"scrappage DB 26-30", 0) Units: veh

(067) "diesel+biodiesel truck share"= 0*TANH (15*policies towards trucks alternative fuels+0) +1 Units: Dmnl

(068) E 25 to 26= DELAY FIXED (E 20 to 21-"scrappage electric 21-25", 5, 0) Units: veh/Year

(069) electric truck share= 0*TANH (15*policies towards trucks alternative fuels+0)+0 Units: Dmnl

(070) electric trucks adoption= truck fleet inflow*electric truck share Units: veh/Year

(071) "ETF 26-30 years old"= INTEG (E 25 to 26-final scrappage-"scrappage electric 26-30", 0) Units: veh

(072) Brazilian freight transport emissions 2020= 7.97e+07 Units: ton

(073) "CO2 budget 1.5ºC"= 4e+11 Units: ton

(074) "control 1.5°C"= IF THEN ELSE (total freight emissions<"% budget 1.5° C Brazilian freight", 0, 1) Units: Dmnl

(075) DBBF 10 to 11= DELAY FIXED (DBBF 5 to 6-"scrappage DBBF 6-10", 5, 0) Units: veh/Year

(076) "DBBF 11-15 years old"= INTEG (DBBF 10 to 11-DBBF 15 to 16-"scrappage DBBF 11-15", 0) Units: veh

(077) DBBF 15 to 16= DELAY FIXED (DBBF 10 to 11-"scrappage DBBF 11-15", 5, 0) Units: veh/Year

(078) "DBBF 16-20 years old"= INTEG (DBBF 15 to 16-DBBF 20 to 21-"scrappage DBBF 16-20", 0) Units: veh

(079) DBBF 20 to 21= DELAY FIXE (DBBF 15 to 16-"scrappage DBBF 16-20", 5, 0) Units: veh/Year

(080) "DBBF 21-25 years old"= INTEG (DBBF 20 to 21-DBBF 25 to 26-"scrappage DBBF 21-25", 0) Units: veh

(081) DBBF 25 to 26= DELAY FIXED (DBBF 20 to 21-"scrappage DBBF 21-25", 5, 0) Units: veh/Year

(082) "DBBF 26-30 years old"= INTEG (DBBF 25 to 26-"scrappage DBBF 26-30", 0) Units: veh

(083) DBBF 5 to 6= DELAY FIXED (biodiesel barge adoption-"scrappage DBBF 0-5", 5, 0) Units: veh/Year

(084) "DBBF 6-10 years old"= INTEG (DBBF 5 to 6-DBBF 10 to 11-"scrappage DBBF 6-10", 0) Units: veh

(085) "DBTR 0-5 years old"= INTEG (biodiesel trains adoption-DBTR 5 to 6-"scrappage DBTR 0-5", 0) Units: veh

(086) DBTR 10 to 11= DELAY FIXED (DBTR 5 to 6-"scrappage DBTR 6-10", 5, 0) Units: veh/Year

(087) "DBTR 11-15 years old"= INTEG (DBTR 10 to 11-DBTR 15 to 16-"scrappage DBTR 11-15", 0) Units: veh

(088) DBTR 15 to 16= DELAY FIXED (DBTR 10 to 11-"scrappage DBTR 11-15", 5, 0) Units: veh/Year

(089) "DBTR 16-20 years old"= INTEG (DBTR 15 to 16-DBTR 20 to 21-"scrappage DBTR 16-20", 0) Units: veh

(090) DBTR 20 to 21= DELAY FIXED (DBTR 15 to 16-"scrappage DBTR 16-20", 5, 0) Units: veh/Year

(091) "DBTR 21-25 years old"= INTEG (DBTR 20 to 21-DBTR 25 to 26-"scrappage DBTR 21-25", 0) Units: veh

(092) DBTR 25 to 26= DELAY FIXED (DBTR 20 to 21-"scrappage DBTR 21-25", 5, 0) Units: veh/Year

(093) "DBTR 26-30 years old"= INTEG (DBTR 25 to 26-"scrappage DBTR 26-30", 0) Units: veh

(094) DBTR 5 to 6= DELAY FIXED (biodiesel trains adoption-"scrappage DBTR 0-5", 5, 0) Units: veh/Year

(095) "DBTR 6-10 years old"= INTEG (DBTR 5 to 6-DBTR 10 to 11-"scrappage DBTR 6-10", 0) Units: veh

(096) diesel barge efficiency= 0.0038 Units: l/(ton*km)

(097) diesel train efficiency= 0.0047 Units: l/(ton*km)

(098) "diesel+biodiesel barge fleet"= "DBBF 0-5 years old"+"DBBF 6-10 years old"+"DBBF 11-15 years old"+"DBBF 16-20 years old" +"DBBF 21-25 years old"+"DBBF 26-30 years old" Units: veh

(099) "diesel+biodiesel barge share"= 0*TANH (15*policies towards barges alternative fuels+0)+1 Units: Dmnl

(100) "diesel+biodiesel TF 0-5 years old"= INTEG (biodiesel trucks adoption-DB 5 to 6-"scrappage DB 0-5", 0) Units: veh

(101) "diesel+biodiesel TF 11-15 years old"= INTEG (DB 10 to 11-DB 15 to 16-"scrappage DB 11-15", 0) Units: veh

(102) "diesel+biodiesel TF 16-20 years old"= INTEG (DB 15 to 16-DB 20 to 21-"scrappage DB 16-20", 0) Units: veh

(103) "diesel+biodiesel TF 21-25 years old"= INTEG (DB 20 to 21-DB 25 to 26-"scrappage DB 21-25", 0) Units: veh

(104) "diesel+biodiesel TF 6-10 years old"= INTEG (DB 5 to 6-DB 10 to 11-"scrappage DB 6-10", 0) Units: veh

(105) "diesel+biodiesel train fleet"= "DBTR 0-5 years old"+"DBTR 6-10 years old"+"DBTR 11-15 years old"+"DBTR 16-20 years old" +"DBTR 21-25 years old"+"DBTR 26-30 years old" Units: veh

(106) "diesel+biodiesel train share"= 0*TANH (15*policies towards trains alternative fuels+0)+1 Units: Dmnl

(107) "diesel+biodiesel truck efficiency"= 0.0577 Units: l/(ton*km)

108) "diesel+biodiesel truck fleet"= "diesel+biodiesel TF 0-5 years old"+"diesel+biodiesel TF 6-10 years old"+"diesel+biodiesel TF 11-15 years old"+"diesel+biodiesel TF 16-20 years old" +"diesel+biodiesel TF 21-25 years old"+"diesel+biodiesel TF 26-30 years old" Units: veh

(109) E 10 to 11= DELAY FIXED (E 5 to 6-"scrappage electric 6-10", 5, 0) Units: veh/Year

(110) E 15 to 16= DELAY FIXED (E 10 to 11-"scrappage electric 11-15", 5, 0) Units: veh/Year

(111) E 20 to 21= DELAY FIXED (E 15 to 16-"scrappage electric 16-20", 5, 0) Units: veh/Year

(112) E 5 to 6= DELAY FIXED (electric trucks adoption-"scrappage electric 0-5", 5, 0) Units: veh/Year

(113) "EBF 0-5 years old"= INTEG (electric barges adoption-EBF 5 to 6-"scrappage electric barge 0-5", 0) Units: veh

(114) EBF 10 to 11= DELAY FIXED (EBF 5 to 6-"scrappage electric barge 6-10", 5, 0) Units: veh/Year

(115) EBF 15 to 16= DELAY FIXED (EBF 10 to 11-"scrappage electric barge 11-15", 5, 0) Units: veh/Year

(116) EBF 20 to 21= DELAY FIXED (EBF 15 to 16-"scrappage electric barge 16-20", 5, 0) Units: veh/Year

(117) "EBF 21-25 years old"= INTEG (EBF 20 to 21-EBF 25 to 26-"scrappage electric barge 21-25", 0) Units: veh

(118) EBF 25 to 26= DELAY FIXED (EBF 20 to 21-"scrappage electric barge 21-25", 5, 0) Units: veh/Year

(119) "EBF 26-30 years old"= INTEG (EBF 25 to 26-"scrappage electric barge 26-30", 0) Units: veh

(120) EBF 5 to 6= DELAY FIXED (electric barges adoption-"scrappage electric barge 0-5", 5, 0) Units: veh/Year

(121) "EBF 6-10 years old"= INTEG (EBF 5 to 6-EBF 10 to 11-"scrappage electric barge 6-10", 0) Units: veh

(122) "EBF 11-15 years old"= INTEG (EBF 10 to 11-EBF 15 to 16-"scrappage electric barge 11-15", 0) Units: veh

(123) "EBF 16-20 years old"= INTEG (EBF 15 to 16-EBF 20 to 21-"scrappage electric barge 16-20", 0) Units: veh

(124) electric barge efficiency= 28 Units: Wh/(ton*km)

(125) electric barge fleet= "EBF 0-5 years old"+"EBF 6-10 years old"+"EBF 11-15 years old"+"EBF 16-20 years old"+"EBF 21-25 years old"+"EBF 26-30 years old" Units: veh

(126) electric barge share= 0*TANH (15*policies towards barges alternative fuels+0)+0 Units: Dmnl

(127) electric barges adoption= barge fleet inflow*electric barge share Units: veh/Year

(128) electric train efficiency= 53.1 Units: Wh/(ton*km)

(129) electric train fleet= "ETR 0-5 years old"+"ETR 6-10 years old"+"ETR 11-15 years old"+"ETR 16-20 years old" +"ETR 21-25 years old"+"ETR 26-30 years old" Units: veh

(130) electric train share= 0*TANH (15*policies towards trains alternative fuels+0)+0 Units: Dmnl

(131) electric trains adoption= train fleet inflow*electric train share Units: veh/Year

(132) electric truck efficiency=1.35 Units: kWh/(ton*km)

(133) electric truck fleet= "ETF 0-5 years old"+"ETF 6-10 years old"+"ETF 11-15 years old"+"ETF 16-20 years old" +"ETF 21-25 years old"+"ETF 26-30 years old" Units: veh

(134) "ETF 0-5 years old"= INTEG (electric trucks adoption-E 5 to 6-"scrappage electric 0-5", 0) Units: veh

(135) "ETF 11-15 years old"= INTEG (E 10 to 11-E 15 to 16-"scrappage electric 11-15", 0) Units: veh

(136) "ETF 16-20 years old"= INTEG (E 15 to 16-E 20 to 21-"scrappage electric 16-20", 0) Units: veh

(137) "ETF 21-25 years old"= INTEG (E 20 to 21-E 25 to 26-"scrappage electric 21-25", 0) Units: veh

(138) "ETF 6-10 years old"= INTEG (E 5 to 6-E 10 to 11-"scrappage electric 6-10", 0) Units: veh

(139) "ETR 0-5 years old"= INTEG (electric trains adoption-ETR 5 to 6-"scrappage electric train 0-5", 0) Units: veh

(140) ETR 10 to 11= DELAY FIXED (ETR 5 to 6-"scrappage electric train 6-10", 5, 0) Units: veh/Year

(141) "ETR 11-15 years old"= INTEG (ETR 10 to 11-ETR 15 to 16-"scrappage electric train 11-15", 0) Units: veh

(142) ETR 15 to 16= DELAY FIXED (ETR 10 to 11-"scrappage electric train 11-15", 5, 0) Units: veh/Year

(143) "ETR 16-20 years old"= INTEG (ETR 15 to 16-ETR 20 to 21-"scrappage electric train 16-20", 0) Units: veh

(144) ETR 20 to 21= DELAY FIXED (ETR 15 to 16-"scrappage electric train 16-20", 5, 0) Units: veh/Year

(145) "ETR 21-25 years old"= INTEG (ETR 20 to 21-ETR 25 to 26-"scrappage electric train 21-25", 0) Units: veh

(146) ETR 25 to 26= DELAY FIXED (ETR 20 to 21-"scrappage electric train 21-25", 5, 0) Units: veh/Year

(147) "ETR 26-30 years old"= INTEG (ETR 25 to 26-"scrappage electric train 26-30", 0) Units: veh

(148) ETR 5 to 6= DELAY FIXED (electric trains adoption-"scrappage electric train 0-5", 5, 0) Units: veh/Year

(149) "ETR 6-10 years old"= INTEG (ETR 5 to 6-ETR 10 to 11-"scrappage electric train 6-10", 0) Units: veh

(150) final scrappage= DELAY FIXED (E 25 to 26-"scrappage electric 26-30", 5, 0) Units: veh/Year

(151) final scrappage CNG= DELAY FIXED (CNG 25 to 26-"scrappage CNG 26-30", 5, 0) Units: veh/Year

(152) final scrappage DB= DELAY FIXED (DB 25 to 26-"scrappage DB 26-30", 5, 0) Units: veh/Year

(153) final scrappage HTF= DELAY FIXED (HTF 25 to 26-"scrappage HTF 26-30", 5, 0) Units: veh/Year

(154) FINAL TIME= 2050 Units: Year The final time for the simulation.

(155) global CO2 emissions 2020= 3.481e+10 Units: ton

(156) HTF 10 to 11= DELAY FIXED (HTF 5 to 6-"scrappage HTF 6-10", 5, 0) Units: veh/Year

(157) HTF 15 to 16= DELAY FIXED (HTF 10 to 11-"scrappage HTF 11-15", 5, 0) Units: veh/Year

(158) HTF 20 to 21= DELAY FIXED (HTF 15 to 16-"scrappage HTF 16-20", 5, 0) Units: veh/Year

(159) HTF 25 to 26= DELAY FIXED (HTF 20 to 21-"scrappage HTF 21-25", 5, 0) Units: veh/Year

(160) HTF 5 to 6= DELAY FIXED (hydrogen trucks adoption-"scrappage HTF 0-5", 5, 0) Units: veh/Year

(161) "hydrogen TF 0-5 years old"= INTEG (hydrogen trucks adoption-HTF 5 to 6-"scrappage HTF 0-5", 0) Units: veh

(162) "hydrogen TF 11-15 years old"= INTEG (HTF 10 to 11-HTF 15 to 16-"scrappage HTF 11-15", 0) Units: veh

(163) "hydrogen TF 16-20 years old"= INTEG (HTF 15 to 16-HTF 20 to 21-"scrappage HTF 16-20", 0) Units: veh

(164) "hydrogen TF 21-25 years old"= INTEG (HTF 20 to 21-HTF 25 to 26-"scrappage HTF 21-25", 0) Units: veh

(165) "hydrogen TF 26-30 years old"= INTEG (HTF 25 to 26-final scrappage HTF-"scrappage HTF 26-30", 0) Units: veh

(166) "hydrogen TF 6-10 years old"= INTEG (HTF 5 to 6-HTF 10 to 11-"scrappage HTF 6-10", 0) Units: veh

(167) hydrogen truck efficiency= 0.1 Units: kg/(ton*km)

(168) hydrogen truck fleet= "hydrogen TF 0-5 years old"+"hydrogen TF 6-10 years old"+"hydrogen TF 11-15 years old" +"hydrogen TF 16-20 years old"+"hydrogen TF 21-25 years old"+"hydrogen TF 26-30 years old" Units: veh

(169) hydrogen truck share= 0*TANH (15*policies towards trucks alternative fuels+0)+0 Units: Dmnl

(170) hydrogen trucks adoption= truck fleet inflow*hydrogen truck share Units: veh/Year

(171) ideal barge fleet= waterway transport activity/"tkm/barge" Units: veh

(172) ideal train fleet= rail transport activity/"tkm/train" Units: veh

(173) ideal truck fleet= road transport activity/"tkm/truck" Units: veh

(174) initial freight transport activity= 1.745e+12 Units: ton*km

(175) INITIAL TIME= 2020 Units: Year The initial time for the simulation.

(176) old barge fleet= INTEG (-old barge scrappage rate, 2709) Units: veh

(177) old barge scrappage rate= old barge fleet*barges scrappage rate/year Units: veh/Year

(178) policies towards alternative modes= RAMP(0.0666667, 2020, 2035) Units: Dmnl

(179) policies towards barges alternative fuels= RAMP (0.033, 2020, 2050) Units: Dmnl

(180) policies towards speeding up fleet renewal= RAMP (0.2, 2020, 2025) Units: Dmnl

(181) policies towards trains alternative fuels= RAMP (0.033, 2020, 2050) Units: Dmnl

(182) policies towards trucks alternative fuels= RAMP (0.0666667, 2020, 2035) Units: Dmnl

(183) rail CO2 emissions= INTEG (rail diesel emissions+rail electricity emissions), 7e+06) Units: ton

(184) rail diesel emissions= train diesel consumption*"rail diesel KgCO2/L"*"ton/kg"/year Units: ton/Year

(185) "rail diesel KgCO2/L"= 2.697 Units: kg/l

(186) rail electricity emissions= train electricity consumption*"rail electricity KgCO2/Wh"*"ton/kg"/year Units: ton/Year

(187) "rail electricity KgCO2/Wh"= 0 Units: kg/Wh

(188) rail share= 0*TANH (15*policies towards alternative modes+0)+0.22 Units: Dmnl

(189) rail transport activity= yearly freight transport activity*rail share) Units: ton*km

(190) "road biodiesel KgCO2/L"= 2.431 Units: kg/l

(191) road biomethane CO2 emission factor= 0.24 Units: kg/m³

(192) road biomethane emissions= truck biomethane consumption*road biomethane CO2 emission factor*"ton/kg"/year Units: ton/Year

(193) "road CNG CO2 emission factor"= 2.101 Units: kg/m³

194) "road CNG emissions"= "truck CNG consumption"*"road CNG CO2 emission factor"*"ton/kg"/year Units: ton/Year

(195) road CO2 emissions= INTEG (road hydrogen emissions+road biomethane emissions+"road CNG emissions" +"road diesel+biodiesel emissions"+road electricity emissions), 6.72e+07) Units: ton

(196) "road diesel KgCO2/L"= 2.697 Units: kg/l

(197) "road diesel+biodiesel CO2 emission factor"= "road biodiesel KgCO2/L"*"% biodiesel in diesel")+"road diesel KgCO2/L"* (1-"% biodiesel in diesel") Units: kg/l

(198) "road diesel+biodiesel emissions"= "truck diesel+biodiesel consumption"*"road diesel+biodiesel CO2 emission factor" *"ton/kg"/year Units: ton/Year

(199) road electricity CO2 emission factor= 0 Units: kg/kWh

(200) road electricity emissions= truck electricity consumption*road electricity CO2 emission factor*"ton/kg" /year Units: ton/Year

(201) road hydrogen CO2 emission factor= 0 Units: kg/kg

(202) road hydrogen emissions= truck hydrogen consumption*road hydrogen CO2 emission factor*"ton/kg"/year Units: ton/Year

(203) road share= 0*TANH (15*policies towards alternative modes+0)+0.63 Units: Dmnl

(204) road transport activity= (yearly freight transport activity*road share) Units: ton*km

(205) SAVEPER = 1 Units: Year [0,?] The frequency with which output is stored.

(206) "scrappage CNG 0-5"= "CNG/biomethane trucks adoption"*"truck scrappage rate 0-5" Units: veh/Year

(207) "scrappage CNG 11-15"= CNG 10 to 11*"truck scrappage rate 11-15" Units: veh/Year

(208) "scrappage CNG 16-20"= CNG 15 to 16*"truck scrappage rate 16-20" Units: veh/Year

(209) "scrappage CNG 21-25"= CNG 20 to 21*"truck scrappage rate 21-25" Units: veh/Year

(210) "scrappage CNG 26-30"= CNG 25 to 26*"truck scrappage rate 26-30" Units: veh/Year

(211) "scrappage CNG 6-10"= CNG 5 to 6*"truck scrappage rate 6-10" Units: veh/Year

(212) "scrappage DB 0-5"= biodiesel trucks adoption*"truck scrappage rate 0-5" Units: veh/Year

(213) "scrappage DB 11-15"= DB 10 to 11*"truck scrappage rate 11-15" Units: veh/Year

(214) "scrappage DB 16-20"= DB 15 to 16*"truck scrappage rate 16-20" Units: veh/Year

(215) "scrappage DB 21-25"= DB 20 to 21*"truck scrappage rate 21-25" Units: veh/Year

(216) "scrappage DB 26-30"= DB 25 to 26*"truck scrappage rate 26-30" Units: veh/Year

(217) "scrappage DB 6-10"= DB 5 to 6*"truck scrappage rate 6-10" Units: veh/Year

(218) "scrappage DBBF 0-5"= biodiesel barge adoption*"barge scrappage rate 0-5" Units: veh/Year

(219) "scrappage DBBF 11-15"= DBBF 10 to 11*"barge scrappage rate 11-15" Units: veh/Year

(220) "scrappage DBBF 16-20"= DBBF 15 to 16*"barge scrappage rate 16-20" Units: veh/Year

(221) "scrappage DBBF 21-25"= DBBF 20 to 21*"barge scrappage rate 21-25" Units: veh/Year

(222) "scrappage DBBF 26-30"= DBBF 25 to 26*"barge scrappage rate 26-30" Units: veh/Year

(223) "scrappage DBBF 6-10"= DBBF 5 to 6*"barge scrappage rate 6-10" Units: veh/Year

(224) "scrappage DBTR 0-5"= biodiesel trains adoption*"train scrappage rate 0-5" Units: veh/Year

(225) "scrappage DBTR 11-15"= DBTR 10 to 11*"train scrappage rate 11-15" Units: veh/Year

(226) "scrappage DBTR 16-20"= DBTR 15 to 16*"train scrappage rate 16-20" Units: veh/Year

(227) "scrappage DBTR 21-25"= DBTR 20 to 21*"train scrappage rate 21-25" Units: veh/Year

(228) "scrappage DBTR 26-30"= DBTR 25 to 26*"train scrappage rate 26-30" Units: veh/Year

(229) "scrappage DBTR 6-10"= DBTR 5 to 6*"train scrappage rate 6-10" Units: veh/Year

(230) "scrappage electric 0-5"= electric trucks adoption*"truck scrappage rate 0-5" Units: veh/Year

(231) "scrappage electric 11-15"= E 10 to 11*"truck scrappage rate 11-15" Units: veh/Year

(232) "scrappage electric 16-20"= E 15 to 16*"truck scrappage rate 16-20" Units: veh/Year

(233) "scrappage electric 21-25"= E 20 to 21*"truck scrappage rate 21-25" Units: veh/Year

(234) "scrappage electric 26-30"= E 25 to 26*"truck scrappage rate 26-30" Units: veh/Year

(235) "scrappage electric 6-10"= E 5 to 6*"truck scrappage rate 6-10" Units: veh/Year

(236) "scrappage electric barge 0-5"= electric barges adoption*"barge scrappage rate 0-5" Units: veh/Year

(237) "scrappage electric barge 11-15"= EBF 10 to 11*"barge scrappage rate 11-15" Units: veh/Year

(238) "scrappage electric barge 16-20"= EBF 15 to 16*"barge scrappage rate 16-20" Units: veh/Year

(239) "scrappage electric barge 21-25"= EBF 20 to 21*"barge scrappage rate 21-25" Units: veh/Year

(240) "scrappage electric barge 26-30"= EBF 25 to 26*"barge scrappage rate 26-30" Units: veh/Year

(241) "scrappage electric barge 6-10"= EBF 5 to 6*"barge scrappage rate 6-10" Units: veh/Year

(242) "scrappage electric train 0-5"= electric trains adoption*"train scrappage rate 0-5" Units: veh/Year

(243) "scrappage electric train 11-15"= ETR 10 to 11*"train scrappage rate 11-15" Units: veh/Year

(244) "scrappage electric train 16-20"= ETR 15 to 16*"train scrappage rate 16-20" Units: veh/Year

(245) "scrappage electric train 21-25"= ETR 20 to 21*"train scrappage rate 21-25" Units: veh/Year

(246) "scrappage electric train 26-30"= ETR 25 to 26*"train scrappage rate 26-30" Units: veh/Year

(247) "scrappage electric train 6-10"= ETR 5 to 6*"train scrappage rate 6-10" Units: veh/Year

(248) "scrappage HTF 0-5"= hydrogen trucks adoption*"truck scrappage rate 0-5" Units: veh/Year

(249) "scrappage HTF 11-15"= HTF 10 to 11*"truck scrappage rate 11-15" Units: veh/Year

(250) "scrappage HTF 16-20"= HTF 15 to 16*"truck scrappage rate 16-20" Units: veh/Year

(251) "scrappage HTF 21-25"= HTF 20 to 21*"truck scrappage rate 21-25" Units: veh/Year

(252) "scrappage HTF 26-30"= HTF 25 to 26*"truck scrappage rate 26-30" Units: veh/Year

(253) "scrappage HTF 6-10"= HTF 5 to 6*"truck scrappage rate 6-10" Units: veh/Year

(254) "scrappage rate 1960-1969"= "train fleet 1960-1969"*"trains scrappage rate 1960-1969"/year Units: veh/Year

(255) "scrappage rate 1970-1979"= "train fleet 1970-1979"*"trains scrappage rate 1970-1979"/year Units: veh/Year

(256) "scrappage rate 1978-1983"= IF THEN ELSE ("speed up fleet renewal - policy control"=0, "truck fleet 1978-1983" *"trucks scrappage rate 1978-1983"/year, (1+policies towards speeding up fleet renewal)*"truck fleet 1978-1983"* "trucks scrappage rate 1978-1983"/year) Units: veh/Year

(257) "scrappage rate 1980-1989"= "train fleet 1980-1989"*"trains scrappage rate 1980-1989"/year Units: veh/Year

(258) "scrappage rate 1984-1989"= IF THEN ELSE ("speed up fleet renewal - policy control"=0, "truck fleet 1984-1989"*"trucks scrappage rate 1984-1989"/year, (1+policies towards speeding up fleet renewal)*"truck fleet 1984-1989"*"trucks scrappage rate 1984-1989"/year) Units: veh/Year

(259) "scrappage rate 1990-1995"= IF THEN ELSE ("speed up fleet renewal - policy control"=0, "truck fleet 1990-1995" *"trucks scrappage rate 1990-1995"/year, (1+policies towards speeding up fleet renewal)*"truck fleet 1990-1995"* "trucks scrappage rate 1990-1995"/year) Units: veh/Year

(260) "scrappage rate 1990-1999"= "train fleet 1990-1999"*"trains scrappage rate 1990-1999"/year Units: veh/Year

(261) "scrappage rate 1996-2001"= IF THEN ELSE ("speed up fleet renewal - policy control"=0, "truck fleet 1996-2001" * "trucks scrappage rate 1996-2001"/year, (1+policies towards speeding up fleet renewal)*"truck fleet 1996-2001"*"trucks scrappage rate 1996-2001"/year) Units: veh/Year

(262) "scrappage rate 2000-2009"= "train fleet 2000-2009"*"trains scrappage rate 2000-2009"/year Units: veh/Year

(263) "scrappage rate 2002-2007"= IF THEN ELSE ("speed up fleet renewal - policy control"=0, "truck fleet 2002-2007" *"trucks scrappage rate 2002-2007"/year, (1+policies towards speeding up fleet renewal)*"truck fleet 2002-2007"* "trucks scrappage rate 2002-2007"/year) Units: veh/Year

(264) "scrappage rate 2008-2013"= IF THEN ELSE ("speed up fleet renewal - policy control"=0, "truck fleet 2008-2013"*"trucks scrappage rate 2008-2013"/year, (1+policies towards speeding up fleet renewal)*"truck fleet 2008-2013"*"trucks scrappage rate 2008-2013"/year) Units: veh/Year

(265) "scrappage rate 2010-2019"= "train fleet 2010-2019"*"trains scrappage rate 2010-2019"/year Units: veh/Year

(266) "scrappage rate 2014-2019"= IF THEN ELSE ("speed up fleet renewal - policy control"=0, "truck fleet 2014-2019" *"trucks scrappage rate 2014-2019"/year, (1+policies towards speeding up fleet renewal)*"truck fleet 2014-2019"*"trucks scrappage rate 2014-2019"/year) Units: veh/Year

(267) "scrappage rate >1959"= "truck fleet >1960"*"trains scrappage rate >1959"/year Units: veh/Year

(268) "speed up fleet renewal - policy control"= 1 Units: Dmnl

(269) TIME STEP = 0.125 Units: Year [0,?] The time step for the simulation.

(270) "tkm/barge"= 1.13787e+08 Units: (ton*km)/veh

(271) "tkm/train"= 1.03586e+08 Units: (ton*km)/veh

(272) "tkm/truck"= 504249 Units: (ton*km)/veh

(273) "ton/kg"= 1/1000 Units: ton/kg

(274) total barge fleet= "diesel+biodiesel barge fleet"+electric barge fleet+old barge fleet Units: veh

(275) total freight emissions= rail CO2 emissions+road CO2 emissions+waterway CO2 emissions Units: ton

(276) total old train fleet= "truck fleet >1960"+"train fleet 1960-1969"+"train fleet 1970-1979"+"train fleet 1980-1989" +"train fleet 1990-1999"+"train fleet 2000-2009"+"train fleet 2010-2019" Units: veh

(277) total old truck fleet= "truck fleet 1978-1983"+"truck fleet 1984-1989"+"truck fleet 1990-1995"+"truck fleet 1996-2001" +"truck fleet 2002-2007" +"truck fleet 2008-2013"+"truck fleet 2014-2019" Units: veh

(278) total train fleet= "diesel+biodiesel train fleet"+electric train fleet+total old train fleet Units: veh

(279) total truck fleet= total old truck fleet+"diesel+biodiesel truck fleet"+"CNG/biomethane truck fleet" +electric truck fleet+hydrogen truck fleet Units: veh

(280) train diesel consumption= transport performed with diesel train*diesel train efficiency Units: l

(281) train electricity consumption= transport performed with electric train*electric train efficiency Units: Wh

(282) "train fleet 1960-1969"= INTEG (-"scrappage rate 1960-1969", 284) Units: veh

(283) "train fleet 1970-1979"= INTEG (-"scrappage rate 1970-1979", 704) Units: veh

(284) "train fleet 1980-1989"= INTEG (-"scrappage rate 1980-1989", 721) Units: veh

(285) "train fleet 1990-1999"= INTEG (-"scrappage rate 1990-1999", 181) Units: veh

(286) "train fleet 2000-2009"= INTEG (-"scrappage rate 2000-2009", 462) Units: veh

(287) "train fleet 2010-2019"= INTEG (-"scrappage rate 2010-2019", 425) Units: veh

(288) train fleet from 2020 onwards= INTEG (train fleet inflow, 0) Units: veh

(289) train fleet inflow= IF THEN ELSE (total train fleet<ideal train fleet, ideal train fleet-total train fleet)/year, 0) Units: veh/Year

(290) "train scrappage rate 0-5"= 1- (EXP (25.4501-3)/7.97197)+EXP (2*25.4501-3)/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-3)/7.97197)) Units: Dmnl

(291) "train scrappage rate 11-15"= 1- (EXP(25.4501-13)/7.97197)+EXP(2*25.4501-13)/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-13)/7.97197)) Units: Dmnl

(292) "train scrappage rate 16-20"= 1- (EXP(25.4501-18)/7.97197)+EXP(2*25.4501-18)/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-18)/7.97197)) Units: Dmnl

(293) "train scrappage rate 21-25"= 1- (EXP(25.4501-23)/7.97197)+EXP(2*25.4501-23)/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-23)/7.97197)) Units: Dmnl

(294) "train scrappage rate 26-30"= 1- (EXP(25.4501-28)/7.97197)+EXP(2*25.4501-28)/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-28)/7.97197)) Units: Dmnl

(295) "train scrappage rate 6-10"= 1- (EXP(25.4501-8)/7.97197)+EXP(2*25.4501-8)/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-8)/7.97197)) Units: Dmnl

(296) "trains scrappage rate 1960-1969"= 1- (EXP(25.4501-("average train age 1960-1969"/year))/7.97197)+EXP(2*25.4501-"average train age 1960-1969"/year))/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-("average train age 1960-1969"/year))/7.97197)) Units: Dmnl

(297) "trains scrappage rate 1970-1979"= 1-(EXP(25.4501-("average train age 1970-1979"/year))/7.97197)+EXP(2*25.4501- ("average train age 1970-1979"/year))/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-("average train age 1970-1979"/year))/7.97197)) Units: Dmnl

(298) "trains scrappage rate 1980-1989"= 1- (EXP(25.4501-("average train age 1980-1989"/year))/7.97197)+EXP(2*25.4501- ("average train age 1980-1989"/year))/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-("average train age 1980-1989"/year))/7.97197)) Units: Dmnl

(299) "trains scrappage rate 1990-1999"= 1- (EXP(25.4501-("average train age 1990-1999"/year))/7.97197)+EXP(2*25.4501-("average train age 1990-1999"/year))/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-("average train age 1990-1999"/year))/7.97197)) Units: Dmnl

(300) "trains scrappage rate 2000-2009"= 1- (EXP(25.4501-("average train age 2000-2009"/year))/7.97197)+EXP(2*25.4501-"average train age 2000-

2009"/year))/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-("average train age 2000-2009"/year))/7.97197)) Units: Dmnl

(301) "trains scrappage rate 2010-2019"= 1- (EXP(25.4501-("average train age 2010-2019"/year))/7.97197)+EXP(2*25.4501-("average train age 2010-2019"/year))/7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-("average train age 2010-2019"/year))/7.97197)) Units: Dmnl

(302) "trains scrappage rate >1959"= 1-(EXP(25.4501-("average train age >1959"/year))/7.97197)+EXP(2*25.4501-("average train age >1959"/year)) /7.97197))/(EXP(25.4501/7.97197)+EXP(2*25.4501-("average train age >1959"/year))/ 7.97197)) Units: Dmnl

(303) "transport performed with CNG/biomethane truck"= road transport activity*"% CNG/biomethane truck" Units: ton*km

(304) transport performed with diesel barge= waterway transport activity*"% diesel+biodiesel barge" Units: ton*km

(305) transport performed with diesel train= rail transport activity*"% diesel+biodiesel train" Units: ton*km

(306) "transport performed with diesel+biodiesel truck"= road transport activity*"% diesel+biodiesel truck" Units: ton*km

(307) transport performed with electric barge= waterway transport activity*"% electric barge" Units: ton*km

(308) transport performed with electric train= rail transport activity*"% electric train" Units: ton*km

(309) transport performed with electric truck= road transport activity*"% electric truck" Units: ton*km

(310) transport performed with hydrogen truck= road transport activity*"% hydrogen truck" Units: ton*km

(311) truck biomethane consumption= "transport performed with CNG/biomethane truck"*biomethane truck efficiency*0.3 Units: m³

(312) "truck CNG consumption"= "transport performed with CNG/biomethane truck"*"CNG truck efficiency" *0.7 Units: m³

(313) "truck diesel+biodiesel consumption"= "transport performed with diesel+biodiesel truck"*"diesel+biodiesel truck efficiency" Units: l

(314) truck electricity consumption= transport performed with electric truck*electric truck efficiency Units: kWh

(315) "truck fleet 1978-1983"= INTEG (-"scrappage rate 1978-1983", 486) Units: veh

(316) "truck fleet 1984-1989"= INTEG (-"scrappage rate 1984-1989", 4869) Units: veh

(317) "truck fleet 1990-1995"= INTEG (-"scrappage rate 1990-1995", 41784) Units: veh

(318) "truck fleet 1996-2001"= INTEG (-"scrappage rate 1996-2001", 217737) Units: veh

(319) "truck fleet 2002-2007"= INTEG (-"scrappage rate 2002-2007", 412363) Units: veh

(320) "truck fleet 2008-2013"= INTEG (-"scrappage rate 2008-2013", 770755) Units: veh

(321) "truck fleet 2014-2019"= INTEG (-"scrappage rate 2014-2019", 453988) Units: veh

(322) "truck fleet >1960"= INTEG (-"scrappage rate >1959", 171) Units: veh

(323) truck fleet inflow= IF THEN ELSE (total truck fleet<ideal truck fleet, (ideal truck fleet-total truck fleet)/year, 0) Units: veh/Year

(324) truck hydrogen consumption= transport performed with hydrogen truck*hydrogen truck efficiency Units: kg

(325) truck sale from 2020 onwards= INTEG (truck fleet inflow, 0) Units: veh

(326) "truck scrappage rate 0-5"= 1- (1/(1+EXP(0.1*(3-17)))+1/(1+EXP(0.1*(3+17)))) Units: Dmnl

(327) "truck scrappage rate 11-15"= 1- (1/(1+EXP(0.1*(13-17)))+1/(1+EXP(0.1*(13+17)))) Units: Dmnl

(328) "truck scrappage rate 16-20"= 1-(1/(1+EXP(0.1*(18-17)))+1/(1+EXP(0.1*(18+17)))) Units: Dmnl

(329) "truck scrappage rate 21-25"= 1-(1/(1+EXP(0.1*(23-17)))+1/(1+EXP(0.1*(23+17)))) Units: Dmnl

(330) "truck scrappage rate 26-30"= 1-(1/(1+EXP(0.1*(28-17)))+1/(1+EXP(0.1*(28+17)))) Units: Dmnl

(331) "truck scrappage rate 6-10"= 1- (1/(1+EXP(0.1*(8-17)))+1/(1+EXP(0.1*(8+17)))) Units: Dmnl

(332) "trucks scrappage rate 1978-1983"= 1- (1/(1+EXP(0.1*("average truck age 1978-1983"/year-17)))+1/(1+EXP(0.1*("average truck age 1978-1983"/year+17)))) Units: Dmnl

(333) "trucks scrappage rate 1984-1989"= 1-(1/(1+EXP(0.1*("average truck age 1984-1989"/year-17)))+1/(1+EXP(0.1*("average truck age 1984-1989"/year+17)))) Units: Dmnl

(334) "trucks scrappage rate 1990-1995"= 1-(1/(1+EXP(0.1*("average truck age 1990-1995"/year-17)))+1/(1+EXP(0.1*("average truck age 1990-1995"/year+17)))) Units: Dmnl

(335) "trucks scrappage rate 1996-2001"= 1-(1/(1+EXP(0.1*("average truck age 1996-2001"/year-17)))+1/(1+EXP(0.1*("average truck age 1996-2001"/year+17)))) Units: Dmnl

(336) "trucks scrappage rate 2002-2007"= 1-(1/(1+EXP(0.1*("average truck age 2002-2007"/year-17)))+1/(1+EXP(0.1*("average truck age 2002-2007"/year+17)))) Units: Dmnl

(337) "trucks scrappage rate 2008-2013"= 1-(1/(1+EXP(0.1*("average truck age 2008-2013"/year-17)))+1/(1+EXP(0.1*("average truck age 2008-2013"/year+17)))) Units: Dmnl

(338) "trucks scrappage rate 2014-2019"= 1-(1/(1+EXP(0.1*("average truck age 2014-2019"/year-17)))+1/(1+EXP(0.1*("average truck age 2014-2019"/year+17)))) Units: Dmnl

(339) waterway CO2 emissions= INTEG(waterway diesel emissions+waterway electricity emissions), 5.5e+06) Units: ton

(340) waterway diesel emissions= barge diesel consumption*"waterway diesel KgCO2/L"*"ton/kg"/year Units: ton/Year

(341) "waterway diesel KgCO2/L"= 2.697 Units: kg/l

(342) waterway electricity emissions= barge electricity consumption*"waterway electricity KgCO2/Wh"*"ton/kg"/year Units: ton/Year

(343) "waterway electricity KgCO2/Wh"= 0 Units: kg/Wh

(344) waterway share= 0*TANH (15*policies towards alternative modes+0)+0.15 Units: Dmnl

(345) waterway transport activity= (yearly freight transport activity*waterway share) Units: ton*km

(346) year= 1 Units: Year

(347) yearly freight transport activity= INTEG (yearly freight transport activity inflow, initial freight transport activity) Units: ton*km

(348) yearly freight transport activity change= 0.0343   Units: 1/Year

(349) yearly freight transport activity inflow= yearly freight transport activity*yearly freight transport activity change   Units: ton*km/Year

B. Appendix B – Policies equations

This appendix presents the policy equations used for each scenario simulation in the model developed in Chapter 4. Table B.1 shows the model equations for policies toward alternative modes; Table B.2 presents the equations for policies toward alternative fuels; and Table B.3 presents the equations for policies toward increasing the percentage of biodiesel in the diesel blend.

Table B.1 – Equations for modal share and policies toward alternative modes*.

Modes	**BAU**	**Setup 1**	**Setup 2**	**Setup 3**
Roadway	0*Tanh(15x+0)+0.63	-0.04*Tanh(15x-7.5)+ 0.59	-0.12*Tanh(15x-7.5)+0.51	-0.16* Tanh(15x-7.5)+0.48
Railway	0*Tanh(15x+0)+0.22	0.05*Tanh(15x-7.5)+0.26	0.10*Tanh(15x-7.5)+0.32	0.13* Tanh(15x-7.5)+0.34
Waterway	0*Tanh(15x+0)+0.15	-0.01*Tanh(15x-7.5)+0.14	0.01* Tanh(15x-7.5)+0.16	0.02* Tanh(15x-7.5)+0.17

*where x in the equations represents the variable “policies toward alternative modes”.

Table B.2 – Equations for fuel share and policies toward alternative fuels*.

Modes	**Fuels**	**BAU**	**Setup 1**	**Setup 2**	**Setup 3**
Roadway	Diesel/biodiesel	0*Tanh(15x+0)+1	-0.07*Tanh(15x-7.5)+0.93	-0.16*Tanh(15x-7.5)+0.84	-0.5*Tanh(15x-7.5)+0.5
	Natural gas/biomethane	0*Tanh (15x+0)+0	0.035*Tanh(15x-7.5)+0.035	0.05*Tanh(15x-7.5)+0.05	0.25*Tanh(15x-7.5)+0.25
	Electricity	0*Tanh (15x+0)+0	0.035*Tanh(15x-7.5)+0.035	0.075*Tanh(15x-7.5)+0.075	0.2*Tanh(15x-7.5)+0.2
	Hydrogen	0*Tanh (15x+0)+0	0*Tanh (15x+0)+0	0.035*Tanh(15x-7.5)+0.035	0.05*Tanh(15x-7.5)+0.05
Railway and Waterway	Diesel	0*Tanh(15x+0)+1	0*Tanh(15x+0)+1	-0.25*Tanh (15x-7.5)+0.75	-0.5*Tanh(15x-7.5)+0.5
	Electricity	0*Tanh (15x+0)+0	0*Tanh(15x+0)+0	0.25*Tanh (15x-7.5)+0.25	0.5*Tanh (15x-7.5)+0.5

*where x in the equations represents the variable “policies toward alternative fuels”.

Table B.3 – Equations for policies toward increasing the percentage of biodiesel in diesel blend*.

Fuels	**BAU**	**Setup 1**	**Setup 2**
Diesel	0*Tanh(15x+0)+0.88	-0.03*Tanh(15x-7.5)+0.85	-0.09*Tanh(15x-7.5)+0.79
Biodiesel	0*Tanh(15x+0)+0.12	0.03*Tanh(15x-7.5)+0.15	0.09*Tanh(15x-7.5)+0.21

*where x in the equations represents the variable “policies toward alternative fuels”.

C. Appendix C – Model results

This appendix presents the results of the total freight emissions, the main output of the simulation model developed in Chapter 4.

Table C.1 – Results of total freight emissions in Scenarios collection 1 (Scenarios 1-8).

Time (Year)	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
2020	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000
2021	258,749,920	258,974,432	261,473,872	258,974,496	258,974,496	258,974,496	258,974,496	258,974,496
2022	444,034,112	444,490,720	449,576,480	444,491,168	444,491,136	444,491,136	444,491,168	444,491,136
2023	635,768,832	636,463,872	644,225,152	636,467,328	636,467,136	636,467,264	636,467,328	636,467,200
2024	834,172,992	835,101,120	845,624,384	835,127,488	835,126,592	835,127,744	835,127,616	835,126,656
2025	1,039,434,688	1,040,500,672	1,053,830,976	1,040,702,400	1,040,696,512	1,040,705,088	1,040,702,400	1,040,695,424
2026	1,251,465,088	1,251,901,696	1,267,755,136	1,253,418,624	1,253,379,712	1,253,439,744	1,253,415,680	1,253,363,328
2027	1,468,412,288	1,463,168,000	1,479,145,088	1,473,425,024	1,473,156,224	1,473,579,776	1,473,408,128	1,473,054,336
2028	1,683,982,336	1,654,641,536	1,661,738,496	1,700,513,024	1,699,032,960	1,701,379,840	1,700,599,552	1,699,011,712
2029	1,897,067,136	1,822,409,856	1,810,240,000	1,934,094,208	1,928,984,448	1,937,098,880	1,935,185,792	1,931,289,600
2030	2,114,253,824	1,985,935,232	1,950,481,536	2,174,042,112	2,162,206,464	2,180,994,304	2,177,768,960	2,171,141,376
2031	2,338,436,608	2,153,433,088	2,093,313,536	2,420,583,936	2,398,826,752	2,433,299,712	2,428,769,280	2,419,256,832
2032	2,570,343,168	2,326,514,432	2,240,787,712	2,673,704,960	2,638,304,000	2,694,136,320	2,688,505,088	2,675,998,976
2033	2,810,313,472	2,505,587,456	2,393,350,400	2,933,642,752	2,880,750,336	2,963,341,056	2,957,284,096	2,941,678,848
2034	3,058,637,312	2,690,890,752	2,551,218,688	3,200,939,008	3,127,059,200	3,240,149,504	3,235,421,696	3,216,609,280
2035	3,315,607,552	2,882,645,504	2,714,582,784	3,476,140,544	3,378,096,384	3,522,776,064	3,523,243,776	3,501,112,320
2036	3,581,525,248	3,081,076,736	2,883,635,200	3,759,532,800	3,633,969,664	3,808,029,696	3,821,087,488	3,795,521,536
2037	3,856,701,952	3,286,417,408	3,058,573,568	4,051,093,504	3,893,887,744	4,090,599,424	4,129,302,016	4,100,182,016
2038	4,141,459,968	3,498,907,648	3,239,603,456	4,351,167,488	4,158,061,056	4,365,820,416	4,448,248,320	4,415,450,112
2039	4,436,133,376	3,718,796,800	3,426,936,320	4,660,390,400	4,427,544,576	4,631,850,496	4,778,299,904	4,741,696,000
2040	4,741,066,752	3,946,342,144	3,620,792,320	4,979,362,304	4,703,312,384	4,889,165,312	5,119,843,840	5,079,301,632
2041	5,056,617,472	4,181,810,688	3,821,398,016	5,308,423,168	4,985,596,928	5,138,551,808	5,473,280,000	5,428,661,760
2042	5,383,155,712	4,425,477,632	4,028,988,672	5,647,713,280	5,273,985,024	5,378,867,200	5,839,022,080	5,790,187,008
2043	5,721,063,936	4,677,629,440	4,243,807,232	5,997,691,904	5,568,962,560	5,609,763,840	6,217,499,648	6,164,299,776
2044	6,070,737,408	4,938,560,512	4,466,105,856	6,359,033,856	5,871,623,680	5,832,052,736	6,609,155,072	6,551,438,848
2045	6,432,586,240	5,208,577,024	4,696,144,896	6,732,359,680	6,182,893,568	6,047,348,736	7,014,447,616	6,952,058,368
2046	6,807,034,368	5,487,995,392	4,934,193,152	7,118,115,328	6,503,148,032	6,257,054,720	7,433,852,416	7,366,626,304
2047	7,194,520,576	5,777,142,784	5,180,530,688	7,516,646,912	6,832,392,192	6,461,139,968	7,867,859,968	7,795,629,568
2048	7,595,499,008	6,076,358,144	5,435,445,248	7,928,479,232	7,171,169,280	6,660,126,720	8,316,979,712	8,239,570,432
2049	8,010,438,656	6,385,991,680	5,699,235,328	8,354,265,600	7,520,367,104	6,855,054,848	8,781,736,960	8,698,969,088
2050	8,439,826,432	6,706,406,400	5,972,210,688	8,794,621,952	7,880,744,960	7,047,328,768	9,262,676,992	9,174,363,136

Table C.2 – Results of total freight emissions in Scenarios collection 2 (Scenarios 9-17).

Time (Year)	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Scenario 13	Scenario 14	Scenario 15	Scenario 16	Scenario 17
2020	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000
2021	258,749,920	258,749,920	258,749,920	258,974,432	258,974,432	258,974,432	261,473,872	261,473,872	261,473,872
2022	444,034,112	444,034,080	444,034,080	444,490,688	444,490,688	444,490,688	449,576,480	449,576,448	449,576,448
2023	635,768,768	635,768,640	635,768,768	636,463,808	636,463,616	636,463,744	644,225,088	644,224,960	644,225,024
2024	834,172,416	834,171,520	834,172,672	835,100,608	835,099,648	835,100,800	845,623,872	845,622,912	845,624,064
2025	1,039,431,232	1,039,425,280	1,039,433,856	1,040,497,216	1,040,491,328	1,040,499,904	1,053,827,456	1,053,821,568	1,053,830,144
2026	1,251,442,048	1,251,403,392	1,251,463,040	1,251,879,168	1,251,841,280	1,251,899,776	1,267,732,608	1,267,694,592	1,267,753,088
2027	1,468,261,504	1,468,007,808	1,468,407,168	1,463,034,752	1,462,810,752	1,463,163,136	1,479,018,496	1,478,805,376	1,479,140,352
2028	1,683,282,816	1,682,106,752	1,683,970,176	1,654,251,264	1,653,594,880	1,654,631,808	1,661,425,920	1,660,899,584	1,661,729,408
2029	1,895,061,120	1,891,688,064	1,897,040,128	1,821,771,904	1,820,697,344	1,822,392,960	1,809,770,752	1,808,979,200	1,810,223,616
2030	2,109,871,744	2,102,502,656	2,114,190,848	1,985,044,480	1,983,540,224	1,985,905,664	1,949,859,072	1,948,804,096	1,950,451,200
2031	2,330,235,904	2,316,442,880	2,338,269,696	2,152,226,560	2,150,182,912	2,153,377,792	2,092,526,208	2,091,182,848	2,093,257,856
2032	2,556,373,248	2,532,869,888	2,569,838,592	2,324,200,448	2,320,275,712	2,326,307,072	2,239,826,176	2,238,167,040	2,240,683,264
2033	2,788,466,944	2,751,692,032	2,808,795,648	2,500,627,968	2,492,211,968	2,504,714,496	2,391,873,024	2,389,297,408	2,393,008,384
2034	3,026,986,752	2,973,650,176	3,054,471,424	2,681,673,216	2,665,994,496	2,688,064,256	2,548,188,416	2,542,885,120	2,549,724,928
2035	3,272,438,016	3,199,547,136	3,305,319,424	2,867,684,608	2,842,108,928	2,875,140,352	2,708,751,872	2,698,473,984	2,709,594,880
2036	3,525,095,424	3,429,515,008	3,558,432,768	3,058,872,064	3,020,617,216	3,063,705,088	2,873,644,032	2,855,823,872	2,870,369,792
2037	3,784,914,432	3,662,760,960	3,808,695,808	3,255,200,000	3,200,854,784	3,249,403,904	3,042,711,040	3,014,004,480	3,027,985,152
2038	4,052,224,256	3,899,504,896	4,051,772,416	3,456,969,728	3,383,076,096	3,428,624,384	3,216,240,640	3,173,281,024	3,179,892,736
2039	4,327,607,808	4,140,694,784	4,286,633,472	3,664,634,624	3,567,986,688	3,601,223,424	3,394,701,824	3,334,439,168	3,325,916,160
2040	4,611,590,656	4,387,161,088	4,514,164,224	3,878,572,032	3,756,145,152	3,768,274,432	3,578,429,952	3,497,973,760	3,466,555,904
2041	4,904,478,720	4,639,132,672	4,734,757,888	4,099,000,832	3,947,703,552	3,930,380,544	3,767,591,424	3,663,970,560	3,602,041,600
2042	5,206,383,616	4,896,218,112	4,946,791,936	4,326,005,760	4,142,360,576	4,085,677,568	3,962,204,416	3,832,032,512	3,731,264,768
2043	5,517,756,928	5,158,947,328	5,149,971,968	4,560,035,840	4,340,785,152	4,233,788,672	4,162,724,864	4,002,907,392	3,855,124,992
2044	5,839,223,296	5,428,309,504	5,345,754,624	4,801,577,984	4,543,723,520	4,376,407,040	4,369,607,168	4,177,293,824	3,974,405,888
2045	6,171,308,544	5,705,051,136	5,535,816,704	5,050,986,496	4,751,622,656	4,514,991,616	4,583,159,808	4,355,577,344	4,089,774,080
2046	6,514,403,840	5,989,523,968	5,721,008,128	5,308,542,976	4,964,741,632	4,650,508,288	4,803,610,112	4,537,973,760	4,201,860,096
2047	6,868,814,336	6,281,743,872	5,900,834,304	5,574,480,896	5,183,105,536	4,781,977,088	5,031,140,864	4,724,472,320	4,310,632,960
2048	7,235,043,840	6,582,264,320	6,075,798,528	5,849,262,080	5,407,330,816	4,909,518,848	5,266,199,552	4,915,712,000	4,417,121,280
2049	7,613,689,344	6,891,866,624	6,247,312,384	6,133,350,400	5,637,976,064	5,034,462,208	5,509,188,096	5,112,136,192	4,521,504,768
2050	8,005,277,696	7,211,166,720	6,416,720,384	6,427,107,328	5,875,418,112	5,157,886,464	5,760,417,792	5,314,069,504	4,624,198,656

Table C.3 – Results of total freight emissions in Scenarios collection 3 (Scenarios 18-26).

Time (Year)	Scenario 18	Scenario 19	Scenario 20	Scenario 21	Scenario 22	Scenario 23	Scenario 24	Scenario 25	Scenario 26
2020	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000
2021	258,749,920	258,749,920	258,749,920	258,974,432	258,974,432	258,974,432	261,473,856	261,473,856	261,473,856
2022	444,034,080	444,034,080	444,034,080	444,490,656	444,490,656	444,490,656	449,576,448	449,576,448	449,576,448
2023	635,768,576	635,768,576	635,768,576	636,463,424	636,463,424	636,463,424	644,225,024	644,225,024	644,225,024
2024	834,171,008	834,171,008	834,170,944	835,098,176	835,098,112	835,097,984	845,624,000	845,624,000	845,624,000
2025	1,039,420,416	1,039,420,288	1,039,419,904	1,040,480,000	1,040,479,616	1,040,478,592	1,053,829,952	1,053,829,888	1,053,829,824
2026	1,251,361,408	1,251,360,384	1,251,357,824	1,251,756,928	1,251,754,112	1,251,747,328	1,267,752,448	1,267,752,448	1,267,752,192
2027	1,467,717,888	1,467,708,032	1,467,688,576	1,462,250,624	1,462,225,408	1,462,175,488	1,479,138,688	1,479,138,432	1,479,137,920
2028	1,680,898,048	1,680,831,872	1,680,731,648	1,651,321,856	1,651,180,800	1,650,954,112	1,661,725,568	1,661,724,928	1,661,723,648
2029	1,889,249,536	1,888,998,144	1,888,698,240	1,815,826,432	1,815,528,192	1,815,064,320	1,810,215,808	1,810,214,784	1,810,212,864
2030	2,099,808,384	2,099,184,896	2,098,585,856	1,975,801,728	1,975,268,608	1,974,472,576	1,950,434,688	1,950,433,152	1,950,430,592
2031	2,315,319,296	2,314,081,536	2,313,179,648	2,138,499,072	2,136,943,232	2,135,556,352	2,093,218,816	2,093,215,488	2,093,211,648
2032	2,535,723,776	2,533,521,408	2,532,436,736	2,301,890,048	2,298,219,776	2,296,411,904	2,240,510,976	2,240,446,976	2,240,438,784
2033	2,760,984,320	2,757,499,648	2,756,344,576	2,464,384,256	2,457,746,432	2,455,804,928	2,392,177,920	2,391,912,448	2,391,912,704
2034	2,991,596,800	2,986,661,888	2,985,482,752	2,626,613,504	2,616,707,072	2,614,782,464	2,547,229,440	2,546,601,472	2,546,644,480
2035	3,228,117,760	3,221,700,608	3,220,494,080	2,789,468,672	2,776,345,344	2,774,471,680	2,703,693,056	2,702,614,528	2,702,736,384
2036	3,470,705,664	3,462,940,928	3,461,707,776	2,952,899,328	2,936,913,152	2,935,090,176	2,858,325,760	2,857,095,680	2,857,327,360
2037	3,719,042,560	3,710,219,264	3,708,993,536	3,115,441,920	3,097,294,080	3,095,581,440	3,005,720,576	3,005,232,384	3,005,615,360
2038	3,973,493,504	3,963,859,712	3,962,656,000	3,277,734,912	3,258,035,968	3,256,440,320	3,142,015,488	3,142,977,792	3,143,476,480
2039	4,234,926,848	4,224,641,024	4,223,456,512	3,441,583,104	3,420,756,736	3,419,292,928	3,268,086,016	3,271,045,376	3,271,723,264
2040	4,504,045,056	4,493,198,848	4,492,019,200	3,607,911,168	3,586,228,224	3,584,888,064	3,385,968,384	3,391,424,000	3,392,333,824
2041	4,781,322,240	4,769,966,080	4,768,775,168	3,777,257,984	3,754,811,648	3,753,534,208	3,498,114,048	3,506,431,232	3,507,525,120
2042	5,066,949,632	5,055,132,160	5,053,926,912	3,949,385,728	3,926,246,144	3,924,992,768	3,605,378,560	3,616,089,600	3,617,155,840
2043	5,361,273,856	5,349,034,496	5,347,819,008	4,124,691,712	4,100,898,048	4,099,649,280	3,707,246,848	3,719,483,392	3,720,388,864
2044	5,664,920,064	5,652,288,000	5,651,069,952	4,304,038,912	4,279,628,800	4,278,393,344	3,804,730,112	3,817,952,000	3,818,735,616
2045	5,978,458,112	5,965,459,456	5,964,240,896	4,487,943,168	4,462,973,952	4,461,764,608	3,899,055,872	3,913,070,080	3,913,782,016
2046	6,302,350,336	6,289,012,736	6,287,786,496	4,676,823,552	4,651,354,112	4,650,164,224	3,991,816,704	4,006,616,320	4,007,264,768
2047	6,636,934,144	6,623,306,752	6,622,074,368	4,870,756,352	4,844,867,072	4,843,690,496	4,083,699,200	4,099,002,624	4,099,557,632
2048	6,982,564,352	6,968,706,048	6,967,476,736	5,069,799,936	5,043,582,976	5,042,428,928	4,174,331,648	4,189,792,256	4,190,277,120
2049	7,339,730,432	7,325,690,368	7,324,477,952	5,274,219,520	5,247,737,344	5,246,608,896	4,263,925,248	4,279,352,064	4,279,802,368
2050	7,708,978,688	7,694,792,192	7,693,601,792	5,484,506,112	5,457,808,896	5,456,715,264	4,353,200,128	4,368,532,480	4,368,970,752

Table C.4 – Results of total freight emissions in Scenarios collection 4 (Scenarios 27-32).

Time (Year)	Scenario 27	Scenario 28	Scenario 29	Scenario 30	Scenario 31	Scenario 32
2020	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000	79,700,000
2021	258,749,616	258,749,936	258,973,584	258,974,464	261,472,736	261,473,888
2022	443,900,032	444,034,208	444,119,520	444,491,040	449,077,568	449,576,896
2023	624,493,632	635,769,856	605,512,768	636,466,944	602,856,128	644,229,248
2024	796,481,216	834,181,440	733,291,520	835,126,848	708,121,728	845,658,496
2025	972,212,544	1,039,501,056	863,171,776	1,040,702,656	813,634,560	1,054,099,456
2026	1,152,066,944	1,251,968,384	994,064,256	1,253,432,832	919,639,168	1,269,793,024
2027	1,336,133,632	1,471,830,144	1,124,362,368	1,473,560,064	1,019,459,456	1,492,982,784
2028	1,524,817,792	1,699,337,344	1,254,141,824	1,701,324,544	1,111,270,912	1,723,905,280
2029	1,718,975,488	1,934,738,688	1,385,038,080	1,936,943,744	1,198,665,856	1,962,762,752
2030	1,919,189,120	2,178,261,248	1,518,238,720	2,180,558,080	1,284,297,344	2,209,648,896
2031	2,125,626,368	2,430,055,680	1,653,953,664	2,432,080,896	1,368,185,600	2,464,340,736
2032	2,338,132,480	2,690,050,816	1,791,235,072	2,690,792,704	1,447,534,592	2,725,727,232
2033	2,557,005,312	2,957,613,824	1,930,362,752	2,954,411,008	1,522,238,208	2,990,531,072
2034	2,783,099,904	3,230,968,576	2,073,068,160	3,217,526,528	1,596,316,928	3,251,282,432
2035	3,016,881,408	3,507,007,232	2,219,976,704	3,471,243,776	1,670,982,656	3,496,289,024
2036	3,258,414,336	3,783,121,920	2,370,815,232	3,708,449,280	1,745,064,576	3,716,144,640
2037	3,507,522,560	4,059,707,392	2,524,465,920	3,930,564,864	1,815,348,480	3,911,973,888
2038	3,764,515,328	4,339,317,248	2,681,234,688	4,144,604,160	1,882,102,144	4,093,886,720
2039	4,030,223,360	4,624,276,480	2,842,804,224	4,355,985,408	1,949,431,040	4,271,215,616
2040	4,305,102,336	4,916,075,520	3,009,649,408	4,567,454,720	2,018,127,360	4,445,595,648
2041	4,589,317,632	5,215,603,200	3,181,555,456	4,780,257,280	2,087,158,528	4,614,707,200
2042	4,882,898,944	5,523,222,528	3,357,820,160	4,994,348,544	2,154,286,592	4,775,599,104
2043	5,186,214,912	5,839,269,888	3,538,801,408	5,209,739,776	2,219,964,416	4,926,423,040
2044	5,499,968,512	6,164,208,128	3,725,761,792	5,426,958,848	2,287,111,680	5,067,566,080
2045	5,824,617,472	6,498,626,560	3,919,105,280	5,646,937,088	2,356,249,088	5,201,404,928
2046	6,160,468,992	6,843,103,232	4,118,820,864	5,870,482,944	2,426,835,712	5,329,761,792
2047	6,507,782,656	7,198,022,144	4,324,692,480	6,097,668,608	2,497,806,848	5,452,154,880
2048	6,866,979,840	7,563,819,520	4,537,049,088	6,328,728,576	2,569,465,344	5,568,507,904
2049	7,238,636,032	7,941,024,256	4,756,646,400	6,564,244,992	2,643,244,032	5,679,786,496
2050	7,623,225,856	8,330,252,800	4,983,853,568	6,805,086,720	2,719,496,192	5,788,018,176

Table C.5 – Results of total freight emissions in Scenarios collection 5 (Scenarios 33-35).

Time (Year)	Scenario 33	Scenario 34	Scenario 35
2020	79,700,000	79,700,000	79,700,000
2021	258,513,136	264,831,968	261,656,784
2022	436,754,400	464,510,272	450,511,232
2023	614,422,848	679,874,368	645,741,824
2024	791,499,904	912,129,408	846,435,392
2025	967,837,952	1,162,385,280	1,055,254,976
2026	1,142,369,024	1,430,372,480	1,270,240,384
2027	1,308,535,296	1,706,306,688	1,485,756,160
2028	1,446,865,152	1,954,578,432	1,673,149,056
2029	1,555,198,080	2,165,094,912	1,824,209,280
2030	1,653,698,560	2,372,384,256	1,967,831,168
2031	1,750,309,888	2,592,408,320	2,116,818,816
2032	1,846,362,368	2,829,010,176	2,270,925,056
2033	1,941,999,232	3,083,192,576	2,431,215,104
2034	2,037,144,448	3,354,620,160	2,595,102,464
2035	2,131,635,456	3,641,093,888	2,761,254,144
2036	2,224,937,472	3,937,979,392	2,926,139,904
2037	2,314,372,096	4,237,955,584	3,087,636,992
2038	2,397,991,424	4,535,185,920	3,242,442,752
2039	2,475,913,472	4,828,456,448	3,389,725,184
2040	2,548,854,784	5,118,467,584	3,531,648,256
2041	2,617,122,048	5,406,201,856	3,667,932,672
2042	2,679,697,152	5,690,729,984	3,798,714,624
2043	2,737,222,144	5,972,313,088	3,924,792,320
2044	2,790,641,408	6,253,216,256	4,046,934,272
2045	2,840,671,232	6,535,501,824	4,164,375,808
2046	2,887,589,632	6,821,433,856	4,277,666,816
2047	2,930,960,640	7,111,908,352	4,387,766,784
2048	2,971,591,168	7,407,932,928	4,495,445,504
2049	3,009,996,032	7,711,698,944	4,601,151,488
2050	3,046,544,896	8,025,438,720	4,705,462,784