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System-level impact of electrification on road freight transport efficiency

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This paper explores the system-level impacts of electrification on road freight transport efficiency, a complex concept involving various stakeholders. Electrification adds further complexity by introducing new stakeholders, dynamics, and efficiency variables. The study applies System Dynamics modelling to explore interactions between efficiencies and the impact of electrification. The model is grounded in literature, expert interviews, and workshops, using Swedish data to simulate 2010–2050 for heavy trucks. Results highlight trade-offs among efficiencies and a worse-before-better behaviour in cost, as electrification initially increases costs but results in lower long-term costs. The model allows testing of policy interventions endogenously to explore their dynamic impacts. Findings show two phases of electric truck adoption. Policy analysis suggests focusing on charging infrastructure in the first phase and cost-oriented policies in the second. By increasing system-level understanding, this paper offers valuable knowledge to decision-makers navigating the transition towards a more efficient and sustainable system.

Road freight transport is a major contributor to greenhouse gas emissions and other environmental externalities¹. To accelerate decarbonisation, several climate targets have been introduced. At the EU level, the Fit for 55 package outlines broad emissions reduction goals, alongside specific targets for heavy-duty vehicles^{2,3}. In Sweden, the national climate goal targets a minimum 70% reduction in transport sector emissions by 2030 compared to 2010, with the aim of achieving net-zero emissions by 2045⁴. Among the various decarbonisation pathways, the electrification of heavy-duty trucks (from here on referred to as E-trucks) is a promising solution⁵. However, this transition is more than just technological shifts; it is a *system transition* that involves a broad range of stakeholders with diverse roles and goals^{6,7}. Therefore, it is challenging to understand the system-level impacts of electrification on the road freight transport system.

Among the various impacts of electrification, this study focuses specifically on its effect on road freight transport efficiency, often used as a performance metric in academic research, industry practices, and policy agendas⁸. Efficiency serves as a fundamental measure of operational effectiveness and is central to both strategic business decisions and governmental sustainability goals⁹. However, within the context of freight transport, efficiency is a complex, fuzzy concept, with varying definitions among stakeholders and across different system layers^{8,10}.

Several studies on freight efficiency have focused on cost and economic aspects: *efficiency for business*. This includes metrics such as vehicle utilisation, fill rate, and loading time (e.g., refs. 9,11). However, with

sustainability becoming a key consideration in transport planning, a new dimension has emerged: *efficiency for society*, which takes into account fuel consumption and greenhouse gas emissions (e.g., refs. 12,13). The literature highlights the need to move beyond relying on a single performance indicator for efficiency and instead consider trade-offs and rebound effects and adopt a system-level perspective^{14,15}. In response, some studies have proposed frameworks to explore different kinds of efficiency simultaneously, recognising different economic, operational, and environmental metrics^{8,10,16}.

Introducing electrification adds further complexity, bringing in new stakeholders, dynamics, and efficiency variables. To fully understand how electrification affects road freight efficiency, a system-level perspective is essential. This allows us to zoom out and examine the different kinds of efficiency, the dynamic interactions between them, and how electrification impacts them. To accomplish this, we utilised a system dynamics (SD) methodology, which is useful for modelling the dynamics of complex systems and incorporating diverse stakeholder perspectives¹⁷. In the existing literature, some studies applied SD to investigate freight decarbonisation, including the adoption of E-trucks (e.g., refs. 18,19). In particular, SD is effective for exploring the effects of different policy interventions and understanding how these policies shape system behaviour over time. Prior research has explored how various policy levers, such as subsidies, infrastructure investment, and carbon pricing, could impact the electrification paths (e.g., refs. 20,21).

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Although some studies have explored transport efficiency and others have focused on electrification of freight transport, this study aims to complement these studies by adopting a system-level perspective that captures several efficiency variables and examines their interdependencies. By developing an SD model, this study investigates the dynamics between these different efficiency variables and how electrification may change these dynamics or introduce new ones. This analysis also incorporates a policy analysis, evaluating how different interventions influence both efficiency outcomes and E-truck adoption. Therefore, two research questions are posed: (i) How does electrification impact different kinds of efficiencies? and (ii) How do policies impact the adoption of E-trucks and different kinds of efficiencies to achieve a more sustainable transport system?

The contributions of this paper are twofold and lie at both methodological and practical levels. The methodological contribution is to develop an SD model exploring the interplay of different efficiencies and how electrification introduces new dynamics and alters existing ones in the Swedish context. The model integrates various efficiency dimensions from both societal and business perspectives within a dynamic framework, capturing their mutual feedbacks and long-term interactions. The simulation runs from 2010 to 2050, enabling validation against historical data (2010–2023), aligning with the base year of Sweden's climate goal⁴, and providing a reasonable future outlook to ensure sound policy analysis. Moreover, the practical contribution is to highlight the critical role of planning and policymaking in a transition to E-trucks and in improving efficiency variables. Through scenario analysis, the model allows policymakers to understand the impacts of different policies and provides them with helpful actionable insights on the timing and combination of interventions needed to transition to a more sustainable freight transport system.

The rest of this paper is structured as follows: The section “Literature overview” reviews the relevant literature on freight transport efficiency, SD modelling in electrification, and relevant policy interventions. The section “Methods” presents the research methodology, detailing the model development process along with the structure and components of the SD model. The section “Results” presents the simulation results and the effects of different policies on adoption and efficiency outcomes. The section “Discussion” discusses the key findings and takeaways, highlighting the trade-offs between different efficiencies, future studies and limitations.

Literature overview

Road freight transport efficiency as a complex concept

The road freight transport system is a complex system involving many stakeholders operating across multiple layers. Several models have been developed to represent the complex interplay between these stakeholders and layers (e.g., refs. 22,23). Freight transport efficiency, in this context, is a fuzzy and multifaceted concept that can become a wicked problem in a policy context¹⁰. In general, transport efficiency describes how effectively resources (time, space, vehicle, fuel, driver, etc.) are used to move goods relative to the outputs achieved²⁴. Yet, defining and measuring freight efficiency is a challenging task, and each stakeholder tends to adopt its own definition, metrics, and priorities.

Previous studies have examined road freight efficiency from various stakeholder perspectives, including logistics service providers (e.g., ref. 25), shippers (e.g., ref. 26), hauliers (e.g., refs. 27,28), and distributors (e.g., ref. 9). Each perspective emphasises different kinds of efficiency, such as cost-effectiveness, resource utilisation, or environmental performance indicators. However, there seems to be a lack of a common agreed definition of transport efficiency that applies across all stakeholder perspectives.

Several studies on freight transport efficiency are oriented towards the economic benefits of transport efficiency, including vehicle utilisation, fill rate, optimising fleet size, empty running, and loading time^{9,11,28–30}. As sustainability gains importance in transport research, some studies are also examining environmental aspects, considering fuel demand and the connection with greenhouse gas emissions. This focus is motivated greatly by climate change and the possible constraints on emissions and fuel consumption¹⁵. Domagala & Kadlubek¹² expand this

view by proposing a multidimensional framework for assessing road freight efficiency across EU countries. Their analysis connects inputs, such as energy and capital, to outputs like freight volumes and CO₂ emissions. It highlights significant differences in national performance and underscores the importance of selecting appropriate indicators. Other studies have similarly addressed energy and environmental efficiency, including those by refs. 13,31.

The literature highlights the need for caution when relying on single performance indicators, emphasising the importance of considering trade-offs and rebound effects and adopting a system-level perspective. For example, Arvidsson¹⁴ describes the load factor paradox, where increasing load factor may require longer routes or more complex scheduling, which can lead to higher total distances and emissions. Likewise, Brinsmead¹⁵ highlights a trade-off between environmental efficiency, such as lower fuel use and emissions, and service performance factors like speed and reliability. Improving one often comes at the cost of the other, emphasising the need for balanced, system-level design in sustainable freight transport.

To address these complexities, some frameworks have been proposed to explore different kinds of efficiency. Arvidsson¹⁰ presents various transport efficiency measures that affect different stakeholders within the system, such as driver efficiency, vehicle efficiency, and route efficiency. The Network for Transport Measures¹⁶ defines transport efficiency from two perspectives. From a company perspective, the goal is to deliver on time, at the right place, in the right conditions, while meeting certain cost restrictions. From a societal perspective, the negative impacts of transport should be included, such as land use, accidents, resource utilisation, noise, and emissions. Finally, Wehner et al.⁸ propose a multi-system framework for defining road freight transport efficiency, which illustrates that stakeholders at different system levels (e.g., material flow or transport infrastructure levels) work towards diverging goals, resulting in different definitions of freight transport efficiency. Furthermore, the framework includes a governance dimension and accounts for the diverse conditions of different systems and their interconnections. Visual representations of the three frameworks are provided in Supplementary Information 1.

This study aims to complement existing literature by adopting a system-level perspective that accounts for multiple dimensions of efficiency. Rather than focusing on a single variable, the approach captures several efficiency variables and examines their interdependencies within the broader freight system.

System Dynamics models for freight transport electrification and relevant policies

To understand the complex dynamics of different kinds of freight transport efficiency and how electrification impacts them, SD offers an appropriate method for analysing and simulating system behaviour over time¹⁷. Shepherd³² highlights the application of SD in transport, noting that it is especially useful for modelling system-level interactions among various stakeholders. Several studies have applied SD to the decarbonisation of freight systems. Ghisolfi et al.³³ reviewed SD models addressing freight transport decarbonisation. Additionally, Ghisolfi et al.³⁴ and Raoofi et al.⁷ provided conceptual models to understand the dynamics between various subsystems within the freight transport system.

Ghisolfi et al.¹⁸ model alternative fuel and mode adoption in Brazil, showing how policy inertia and slow technological shifts can hinder decarbonisation progress. Shafiei et al.^{35,36} analyse the influence of fiscal incentives on alternative fuel vehicle adoption, revealing how subsidies and taxes shape both consumer decisions and macroeconomic outcomes. Cagliano et al.³⁷ simulate the adoption of electric and hybrid vans in urban logistics, identifying the influence of advertising, social image, and word-of-mouth on market penetration. In operational contexts, Aschauer et al.³⁸ used SD to show how logistics strategies enhance transport operations and reduce environmental impacts, while Thaller et al.³⁹ used causal loop diagrams to map stakeholder relationships and operational dynamics in urban freight. Other modelling approaches, such as the ASTRA model⁴⁰, have been

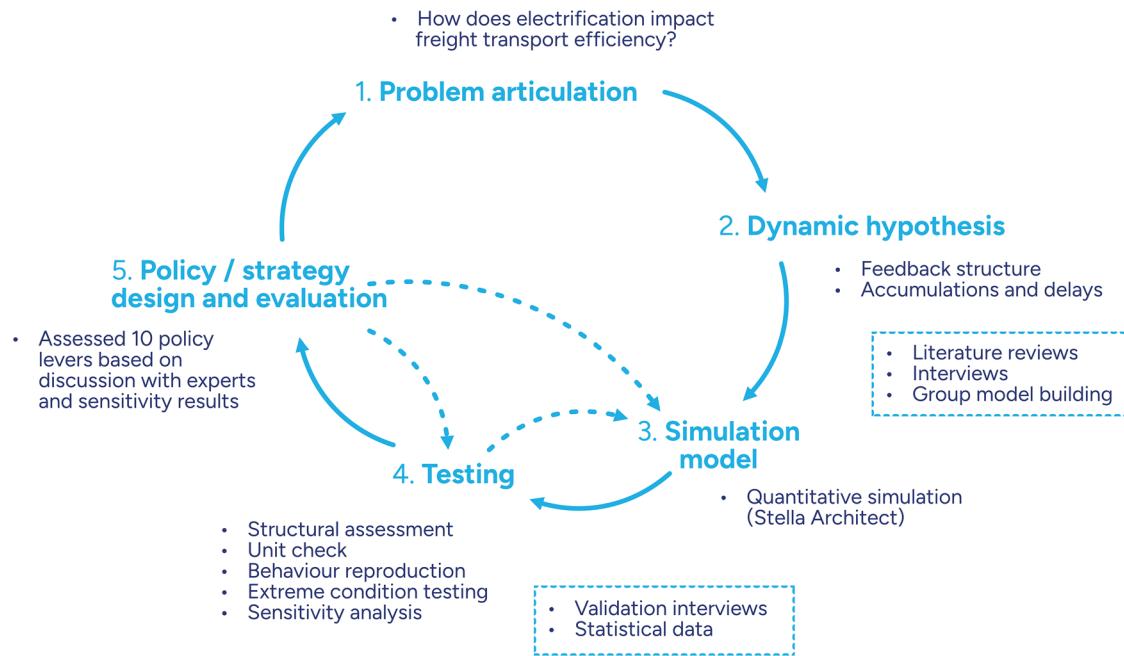


Fig. 1 | Methodological process of the study. A mixed approach of literature review, semi-structured interviews, a group model building workshop, and validation interviews. The figure is based on the standard SD methodological process¹⁷.

used at the EU level for strategic transport and energy policy analysis, simulating interactions among demand, vehicle technology, the economy, and environmental outcomes.

Recently, Raoofi et al.¹⁹, in a closely related study, examined how charging infrastructure availability influences E-truck adoption, with a focus on investment decisions by public and private actors and the effects of five policy levers (charging and vehicle subsidies, technology maturity investments, electricity and diesel price changes). Their study centres on adoption rates, without assessing how electrification affects freight transport efficiency. Moreover, it does not account for potential rebound effects of costs on freight demand.

Furthermore, a number of policy-focused studies underscore the importance of regulatory and economic instruments in driving freight decarbonisation. Ovaere & Proost²¹ evaluate the European Union's *Fit for 55* package, emphasising the importance of vehicle subsidies, carbon pricing, and infrastructure investments in making E-trucks economically viable. Moreover, Breed et al.²⁰ examine how EU CO₂ fleet regulations influence the necessary market share of zero-emission trucks, depending on manufacturer strategy. Liu and Xiao⁴¹ use a scenario-based SD model to analyse how policy incentives, including subsidies, infrastructure provision, and consumer preferences, shape electric vehicle adoption in China. Bian and Xu⁴² demonstrate that policy combinations, such as promoting the green image and implementing carbon tax rebates, can reduce emissions without compromising rural logistics growth. Menezes et al.⁴³ also highlight the necessity of integrated policy mixes to achieve substantial emission cuts in urban transport systems. In a behavioural policy context, Ertelt et al.⁴⁴ show that perceptions of policy neutrality and emotional drivers like anticipated regret can delay managerial decisions to adopt zero-emission trucks in Sweden.

Connecting two bodies of literature on the different kinds of efficiencies and electrification of the road freight transport system, our study adopts a system-level perspective and investigates the dynamics between various transport efficiencies and how electrification may change these dynamics or introduce new ones by developing an SD model. This effort is grounded in the context of sustainability to guide policymakers and decision-makers towards more informed decisions that could lead to a sustainable future transport system.

Methods

System Dynamics (SD), rooted in control theory and systems thinking⁴⁵, is a method for understanding complex systems with many interacting variables and feedback loops¹⁷. As detailed in the section "Literature overview", the road freight transport system is one such complex system. Moreover, it involves multiple stakeholders such as shippers, carriers, infrastructure providers, and the public sector³², making the SD methodology particularly relevant to our study.

To develop the SD model for this study, we followed the standard SD methodological process¹⁷, as shown in Fig. 1 and explained in the text. In total, we engaged 35 experts from public authorities, industry, and academia, as detailed in Supplementary Information 2.

The problem and its boundaries were defined through a literature review (see Supplementary Information 3 for an overview). To further refine the problem and develop the dynamic hypothesis, we conducted eight semi-structured interviews with experts from public authorities, industry, and academia, following the method outlined by Luna-Reyes and Andersen⁴⁶. During the semi-structured interviews, we guided discussions with experts using a predefined set of questions that covered various variables and dynamics (see Supplementary Information 2).

In the next step, a Group Model Building workshop was conducted, involving eleven experts from the public authorities, industry, and academia. Group Model Building is a participatory approach in SD, where stakeholders collaborate to create a dynamic model of a complex system to understand the underlying causes and feedback structures that drive system behaviour^{47–49}. During the workshop, participants were involved in three main activities: eliciting key variables, initiating a causal loop diagram, and understanding the impacts of different policies (see Supplementary Information 2 for descriptions of the activities). Causal Loop Diagrams (CLDs) from different groups in the workshop were the main outcomes.

Building on the insights from the literature, interviews, and workshop, we developed a refined Causal Loop Diagram (CLD) and a simulation model utilising Stella Architect version 3.2.1. These were iterated with the experts through various meetings aimed at evaluating the model's structure, the accuracy of the mathematical equations, and the quality of the exogenous data. Data collection was supported by relevant official authorities and experts in the field.

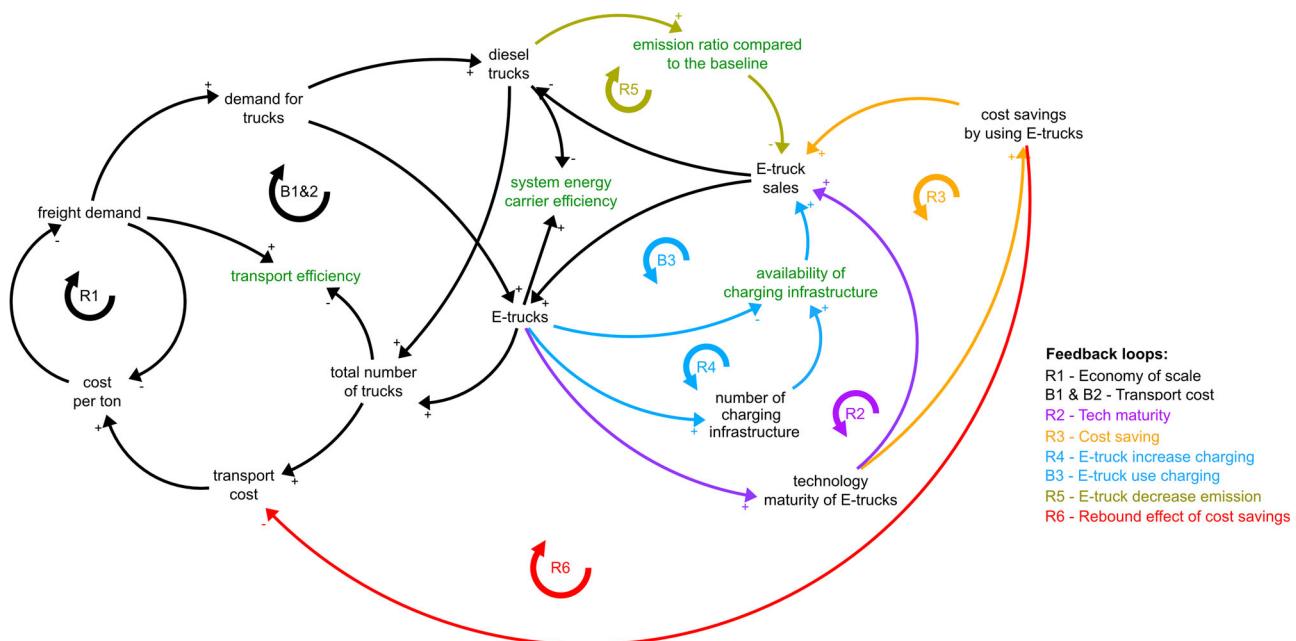


Fig. 2 | The simplified causal loop diagram (CLD). The positive signs on the arrows indicate influence in the same direction; the negative signs on the arrows indicate influence in the opposite direction. The loops are indicated in the legend on the right, and each loop is identified as either a reinforcing (R) or a balancing (B). Supplementary Information 4 provides details on the loops and dynamics of various variables.

To validate the model, we conducted a series of tests, including structural assessment, unit checks, behaviour reproduction, extreme condition tests, and sensitivity analysis, based on Sterman¹⁷. Additionally, we conducted five interviews with experts to confirm the validity of the model (based on Richardson & Pugh⁵⁰). Furthermore, based on the sensitivity analysis and collaborative meetings with experts, various policy levers were developed. These were subsequently evaluated through policy and scenario analyses to assess the impact of different policies on the system.

Model structure: dynamic hypothesis

Figure 2 illustrates the dynamic hypothesis in the form of a Causal Loop Diagram (CLD) and shows the key feedback loops underlying the problem.

The feedback loops in Fig. 2 show that as freight demand (in ton) rises, the demand for trucks increases. Therefore, the supply side reacts by buying new trucks, either diesel or E-trucks. As a result, the total number of trucks rises, increasing the transport cost. The transport cost increases in turn the cost per ton, bringing a decrease in demand. The loops of *transport cost* (B1 & B2) limit the demand growth. In contrast, the *economy of scale* (R1) reinforcing loop illustrates how the growth in freight demand (in ton) reduces transport cost per ton. Lower costs trigger an increase in induced demand due to price changes. Therefore, the higher the freight demand, the lower the cost per ton, further boosting the freight demand (see refs. 51,52). The interplay between the three loops - R1, B1 & B2 - determines if the freight demand increases, decreases, or is in equilibrium. Furthermore, the transport efficiency is related to this interplay, as it is measured as the freight demand divided by the capacity of the supply.

The right side of Fig. 2 depicts the dynamics of the four factors influencing the attractiveness and market share of E-truck sales: the cost savings by using E-trucks, the availability of charging infrastructure, the technology maturity of E-trucks, and the emission ratio compared to the baseline. The cost savings by using E-trucks increase with an increase in technology maturity and positively influence the E-truck sales share. The technology maturity is influenced by the number of E-trucks sold. Therefore, the higher the number of E-trucks, the higher the technology maturity⁵³. This has a dual effect, increasing directly and indirectly (through the cost savings) the E-truck sales share. These two effects are depicted by the loops *Tech maturity* (R2) and *Cost saving* (R3).

and each loop is identified as either a reinforcing (R) or a balancing (B). Supplementary Information 4 provides details on the loops and dynamics of various variables.

Moreover, as more E-trucks enter the market, the demand for charging stations increases⁵⁴. In the *E-trucks use charging* (B3) balancing loop, this increased demand for charging stations results in a reduced availability of charging stations, hindering E-truck sales. However, in the *E-truck increase charging* (R4) reinforcing loop, the surge in demand for charging stations motivates the construction of more stations, consequently increasing availability. This positive feedback loop, in turn, boosts E-truck sales. Finally, the E-truck sales share reduces the number of diesel trucks in the fleet. This reduction in turn reduces the emission ratio compared to the baseline, which boosts E-truck sales share⁵⁵. This dynamic is represented in the reinforcing loop *E-truck decrease emission* (R5).

Main model assumptions

The main model assumptions are as follows.

The definitions of different kinds of efficiencies are based on the literature and the expert opinions. It is important to consider how we define and calculate efficiency when the results are used (see the section “Model Structure: simulation model” for a detailed definition of the efficiency variables).

Four factors are considered as E-truck adoption drivers: cost saving, availability of charging infrastructure, technology maturity, and emission ratio compared to the baseline. In addition, we assume that cost savings influence E-truck adoption once cost parity is achieved. Prior to that, adoption is driven by infrastructure availability, technology maturity, and emission ratio compared to the baseline.

The model is based on the Swedish market and government. The structures have been validated with experts and policymakers based in Sweden.

Only E-trucks and diesel trucks are considered in the model. Hybrid, hydrogen-fuelled, biofuel, and other alternative fuel trucks are not included. This focus was informed by our expert group during the problem articulation phase, where they identified E-trucks as having the greatest potential for emission reduction in the sector, an insight supported by recent literature (e.g., refs. 5,56).

The category of trucks studied includes heavy trucks, defined in Sweden as those weighing over 3.5 tonnes. Additionally, there are no separate classifications within this category; all trucks over 3.5 tonnes are considered

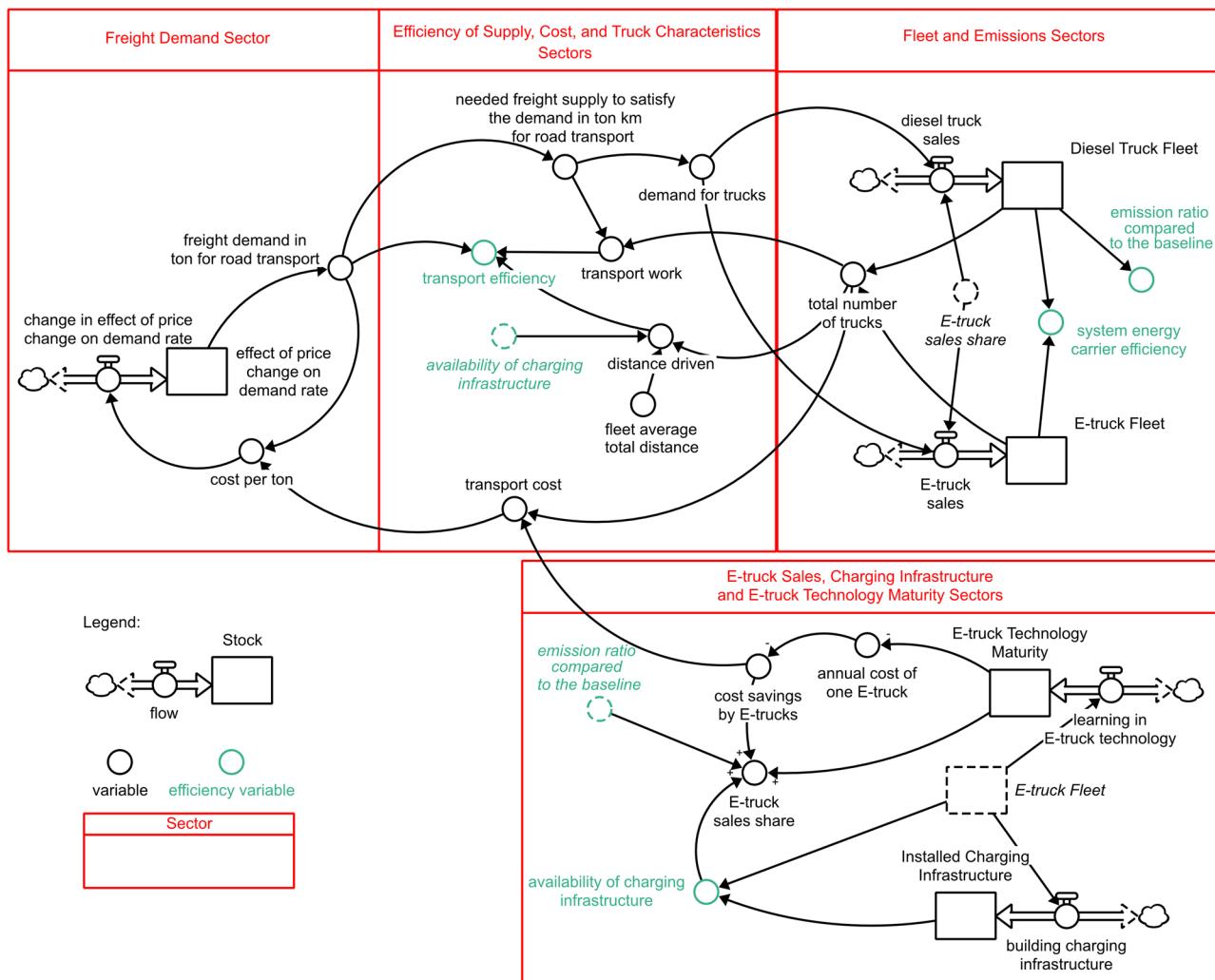


Fig. 3 | Simplified stock and flow diagram. The diagram illustrates nine sectors, with some represented together for simplification. Many variables and arrows are excluded to enhance clarity.

as a single group. This assumption is based on the fact that most Swedish data sources, such as Trafikanalys, SCB, and Trafikverket, aggregate all trucks over 3.5 tonnes into a single category, with limited or inconsistent disaggregation data. Aggregating these subclasses also reduces the complexity of the model and aligns with the system-level scope of the study.

The simulation time spans from 2010 to 2050. Starting from 2010 allows for validation against historical data (2010–2023) and aligns with the base year used in Sweden's climate goal⁴. Extending the model to 2050 provides a reasonable future outlook to ensure sound policy analysis, in line with our expert opinion.

Equal lifetimes of trucks are assumed for E-trucks and diesel trucks⁵⁷, as definitive values for these parameters for E-trucks have not yet been established. However, this parameter, along with others, is adjustable in the model and online interface, enabling users to explore how varying assumptions influence the simulation results.

Different types of stationary charging, including depot, highway, and destination charging, are aggregated in the model. The focus is on the overall impact of charging station availability on E-truck adoption, rather than on the dynamics or competition among specific charging options. In addition, other charging strategies, such as Electric Road Systems (ERS) and battery swapping, are excluded, in line with the focus of EU-level planning initiatives such as the Alternative Fuels Infrastructure Regulation (AFIR) and Sweden's national plan⁵⁸.

Freight demand is calculated by considering the growth in population and a fixed demand rate of each person in one year. Moreover, an elasticity

of -1^{51} is considered to model the variation of demand due to the variation in price.

Model structure: simulation model

The simulation model comprises 268 variables, 165 equations, and 16 stocks, organised into 9 sectors that are described in detail in the following texts. A simple representation of the simulation model is presented in Fig. 3. The Stella Architect version is available in Supplementary Information 5, and full model documentation is provided in Supplementary Information 6. In addition, because efficiency variables are central to this research, a table in Supplementary Information 6 summarises all efficiency variables modelled in the study, along with their definitions, calculation formulas in the SD model, and the impact of electrification.

Freight demand sector is described as follows. The main goal of this sector is to calculate the *freight demand in ton km for road transport*. This is calculated by multiplying the *demand rate*, the *Population of Sweden* and the *AVERAGE DISTANCE WEIGHTED BY TON*. Note that parameters are written in capital letters throughout this section.

- The *demand rate* considers a base demand rate taken from transport statistics⁵⁹, and it is influenced by the *Effect of Price Change on Demand Rate*. This effect is calculated as a stock that takes into account the fractional change in price per ton per year and the elasticity between cost and demand. In practice, this structure gives an increase in demand when prices drop and vice versa. The elasticity is assumed to be constant and equal to -1^{51} .

- The *Population of Sweden* is calculated as a stock to match the population statistics and projections⁶⁰.
- The *AVERAGE DISTANCE WEIGHTED BY TON* variable represents the average distance that each ton travels (from a demand side) in the system. This is not related to any operational value, but rather it measures the average distance between origin and destination. The data is taken from the Samgods PWC matrix⁵⁹, which states all the origins and destinations of trips in the freight transport system of Sweden.

Efficiency of supply sector is described as follows. The goals of this sector are twofold: to calculate the *demand for vehicles* and to calculate the *transport efficiency*. The *demand for vehicles* is calculated considering the needed freight supply to satisfy the demand, which is calculated by multiplying the demand by the *RATIO BETWEEN SUPPLY AND DEMAND*. This ratio represents how much transport work from the supply side is needed to satisfy the demand. This ratio is calculated using data from the Samgods PWC matrix⁵⁹ and Trafikanalys⁶¹. Moreover, when electrification begins, the *total detour in ton km* is also added to the needed supply. This depends on the detour distance per E-truck, which is influenced by the availability of charging infrastructure, calculated within the charging infrastructure sector.

The *transport efficiency* is calculated considering the *freight demand in ton km* and the *maximum possible transport work*. This maximum work is the total transport work that would be possible if all trucks were to operate at maximum capacity (always full) and drive the maximum annual mileage. The *transport efficiency* can be seen as the combination of three other kinds of efficiencies, described below. A summary of all efficiency variables modelled in the study is provided in Supplementary Information 6.

- The *routing efficiency*, which considers the ratio of the *freight demand in ton km* and the *transport work*. The *number of trucks* and the *actual transport work per truck* are used to calculate the *transport work*. Routing efficiency is decreased by the need for E-trucks to take more detours during the early stages of adoption when charging infrastructure is limited. As adoption progresses and charging infrastructure expands, routing efficiency improves, approaching pre-electrification levels.
- The *fill rate*, which considers the ratio of *transport work* and the *potential transport work considering a full load*, where potential transport work is the amount that could be carried out if all trucks were always travelling full. Fill rate decreases in the early stages of E-truck adoption due to the battery weight of E-trucks. As adoption progresses and battery technology matures, battery weight decreases and fill rate improves.
- The *vehicle utilisation*, which considers the ratio of the *potential transport work* considering a full load and the *maximum possible transport work*. Vehicle utilisation decreases due to a reduction in *total available driving time*, as there is some time required during shifts for E-truck detouring, queuing and charging. As more charging infrastructure is built, detouring and queuing time decreases, improving vehicle utilisation. However, vehicle utilisation remains lower than pre-electrification levels due to the charging time required during the shift.

The fleet sector is described as follows. In the fleet sector, the *demand for trucks* and the *E-truck sales share* (explained in the next sector) are used to calculate the *diesel truck sales* and the *E-truck sales*. These sales are inflows to the *Diesel Truck Fleet* and *E-truck Fleet* stocks. In turn, these stocks have truck decommissioning as outflows. The *total number of trucks* is calculated as the sum of the two fleets.

The E-truck Sales sector is described as follows. The E-truck sales share is determined considering four factors: cost savings by using E-trucks, availability of charging infrastructure, E-truck technology maturity, and emission ratio compared to the baseline. Each factor varies from 0 to 1, with 0 corresponding to zero influence and 1 corresponding to maximum

influence. Each factor has a different weight, and an innovator rate of 2.5%⁶² is considered as the base growth rate to start the adoption. In this way, when all four factors reach their maximum, the result is an E-truck sales share of 100%.

- The *cost savings by using E-trucks* are considered in terms of the ratio between the annual cost of one E-truck and one diesel truck. The cost savings are maximum when this ratio reaches the minimum value. Cost-related considerations consistently emerge as a dominant factor in adoption decisions (e.g., refs. 57,63,64).
- The *availability of charging infrastructure* considers the ratio between the number of charging stations and the demand for charging stations by E-trucks. The influence of this availability on E-truck sales is maximum when the availability is 1. Availability of charging infrastructure is also recognised as an important enabler (e.g., refs. 19,54,65).
- The *technology maturity* considers the *ratio of technology maturity to the goal*. This ratio measures the progress of technology maturity compared to the set goal. The influence of maturity is maximum when the ratio is 1. Prior works (e.g., refs. 66,67) point to the significance of vehicle and battery technology maturity.
- The *emission ratio compared to the baseline* considers the emission reduction ratio compared to the emissions during 2010. The influence of the emission is maximum when the emission ratio compared to the baseline is lowest. As E-trucks produce no tailpipe emissions, environmental performance is another motivator for adoption (see e.g., refs. 55,68).

The cost sector is described as follows. In the cost sector, the annual cost of one diesel truck and of one E-truck is calculated, considering the cost of diesel fuel (or of electricity), the maintenance cost, and the annual purchase cost^{63,69}. The *E-truck purchase cost* is calculated in the technology maturity sector and decreases over time. Moreover, the annual employee cost for each vehicle is calculated. These costs allow us to understand the cost parity point between E-trucks and diesel trucks. Moreover, the *annual total cost* is calculated considering the entire fleet, and the *cost per ton* is calculated by dividing the *annual total cost* by the *freight demand in ton*. The *cost per ton* is used in the freight demand sector to understand the rebound effect of a change in cost on the demand for freight transport. Note that a discount rate was not applied when calculating the costs.

The emissions sector is described as follows. In the emissions sector, the *total annual emissions* are calculated as the annual emissions from diesel trucks, considering the distance driven by the diesel truck fleet. The *total annual emissions* are then compared with the *emission level in 2010*⁷⁰, resulting in the *emission ratio compared to the baseline*, which is considered as one kind of efficiency. The reason for this comparison is that Sweden's transport climate target is to reduce emissions by a minimum of 70% by 2030 compared to the levels of 2010⁴. The emissions coming from the production of electricity are omitted, as in Sweden's transport climate target only operational emissions (tank-to-wheel) are considered. Similarly, the emissions from diesel trucks are calculated considering the carbon intensity of diesel fuel, corresponding to the equivalent carbon dioxide emissions per litre of diesel consumed during driving (tank-to-wheel). Naumov et al.⁷¹ used a similar approach to model emissions.

The Truck Characteristics sector is described as follows. In this sector, the characteristics of diesel and E-trucks are calculated separately to be used in the other sectors. The main outputs of this sector are the fleet average load, truck capacity, total distance, and transport work. Each of these variables is a weighted average considering the share of diesel and E-trucks. The load is calculated, including both loaded and empty km. The E-truck capacity is calculated excluding the weight of the battery. The total distance and transport work of the E-trucks are calculated, including the potential detours to charging stations and considering the potential extra time needed for charging.

The Charging Infrastructure sector is described as follows. The infrastructure is planned by considering the current E-truck Fleet and calculating

the current demand for charging stations based on the average station demand per E-truck. The *Installed Charging Stations* is a stock that has an inflow of *building stations* and an outflow of *scrapping stations*. The *TIME TO PLAN AND BUILD A STATION* is considered a delay in the system together with the *LIFETIME OF A CHARGING STATION*^{72,73}.

The *average station demand per E-truck* is calculated using three variables:

- The *kWh consumption of one E-truck* is calculated by multiplying the annual total distance per E-truck by its energy consumption per kilometre.
- The *Average Power of Charging Station* is assumed to increase over time due to technological advancements⁷⁴.
- The *possible utilisation rate of a station* changes over time, bounded between two values. The lower bound reflects the limited and uneven distribution of charging stations during the early phase of E-truck adoption, while the upper bound represents the maximum achievable technical level. As adoption progresses, the utilisation rate gradually transitions from the lower to the upper bound, following the growth in the share of E-trucks.

Two efficiencies related to the charging infrastructure are defined in this sector:

- The availability of charging stations is calculated by dividing the *Installed Charging Stations* by the current demand for charging stations.
- The utilisation rate of charging stations is calculated by dividing the kWh consumption by the E-truck fleet (total annual energy consumption by the E-truck fleet) and the kWh capacity of all installed stations (combined energy capacity of all installed charging stations over a year).

Based on the availability of charging stations, a *queuing time* and a *detour time* are calculated. If the availability is 1, both the queuing and detour times are zero. If the availability is zero, both queuing and detour time are at their maximum value. These variables influence the E-truck characteristics and therefore the efficiency of the system as a whole.

The E-truck Technology Maturity Sector is described as follows. The *E-truck Technology Maturity* is calculated as a stock, with inflow *learning in E-truck technology*, inspired by Nieuwenhuijsen et al.⁵³. The learning is done thanks to *R&D spending* and based on the *TECHNOLOGY IMPROVEMENT PER SEK SPENT*. So for each SEK spent in R&D, the technology maturity accumulates. The *R&D investment* comes from the private sector, and especially from the income from diesel and E-truck sales. The technology maturity influences three variables, which in turn influence the cost and characteristics of E-trucks:

- The *E-truck purchase cost*, which decreases the closer the technology reaches its maturity. The minimum E-truck purchase cost is set as equal to the *DIESEL TRUCK PURCHASE COST*⁶³.
- The *Battery Weight (ton/kWh)*, which decreases the closer the technology reaches its maturity. Both initial and minimum battery weights are taken from Zu & Li⁷⁵ and re-evaluated with updated data from Teichert et al.⁷⁶.
- The *Average Power of Charging Station*, which increases the closer the technology reaches its maturity. Both initial and maximum power are taken from ACEA⁷⁴.

Model validation

To ensure the accuracy and reliability of the simulation model, various validation tests were conducted using the methods proposed by Sterman¹⁷. A structural assessment validation process was conducted through meetings with experts, as mentioned in the methodological process. Moreover, the model passed the unit check function, confirming that the dimensional consistency is respected.

Eight extreme condition tests were carried out, involving setting selected model parameters to extreme values and comparing the behaviour

generated by the model with the expected behaviour, which is available in Supplementary Information 7. In addition, several behaviour reproduction tests were conducted to validate the model against real-world trends. However, behaviour validity is less critical than in classical forecasting models, as the model represents a future system with limited calibration data. A point-by-point match with observed behaviour is neither feasible nor essential. The main results of these tests are presented in Supplementary Information 8. Finally, 26 sensitivity analyses have been conducted to examine the model's responsiveness to changes in parameters for which data was unavailable or limited. Some of these are further explored in the section "Sensitivity analysis"; the rest is reported in Supplementary Information 9. From the sensitivity results, a selection of policies was run. Supplementary Information 10 reports information on all the policies, while the results of the most influential policies are presented in the section "Policy analysis".

All input parameters are obtained from official statistics and relevant scientific research. For transparency and reproducibility, all input data utilised in the model is provided in the model documentation, which can be found in Supplementary Information 6, including detailed references or sources for each input parameter.

Results

In this section, first, the base scenario results are described, depicting the most important dynamics in the system. Then, a comparison between the base scenario and a scenario without E-trucks is performed, followed by a short overview of the sensitivity analysis performed. Finally, the most relevant policies are analysed.

Base scenario results

Fleet size comparison is shown in Fig. 4, illustrating the trends of E-truck and diesel truck fleets in Sweden over time. The total number of trucks shows a nearly linear growth pattern. The E-truck fleet grows exponentially, while the diesel truck fleet expands up to a certain point before gradually declining. The two curves of the diesel and E-truck fleet meet when the two technologies comprise 50% of the total market. After this point and until the end of the simulation, the share of E-trucks is higher than the share of diesel trucks.

Cost parity point is illustrated in Fig. 5, comparing annual costs of E-trucks and diesel trucks, including purchase, maintenance, and operational costs. Initially, E-trucks have significantly higher total costs compared to diesel trucks. However, in the middle of the simulation (around the year 2036), the costs intersect, after which E-trucks have lower total costs than diesel trucks for the remainder of the simulation. Note that the year of cost parity depends on the pace of technology maturity, distance driven, price of electricity, and other model assumptions and should not be viewed as a prediction but as a critical point after which there is a change in behaviour.

E-truck sales development over time is illustrated in Fig. 6. These, as mentioned in the section "Model Structure: simulation model", depend on

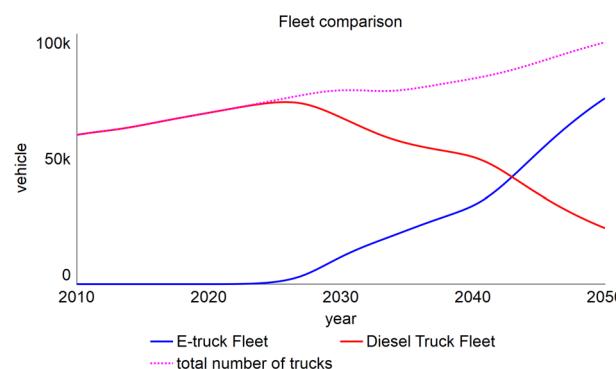


Fig. 4 | Fleet comparison. The figure shows the comparison of E-truck and diesel truck fleets in Sweden, 2010–2050.

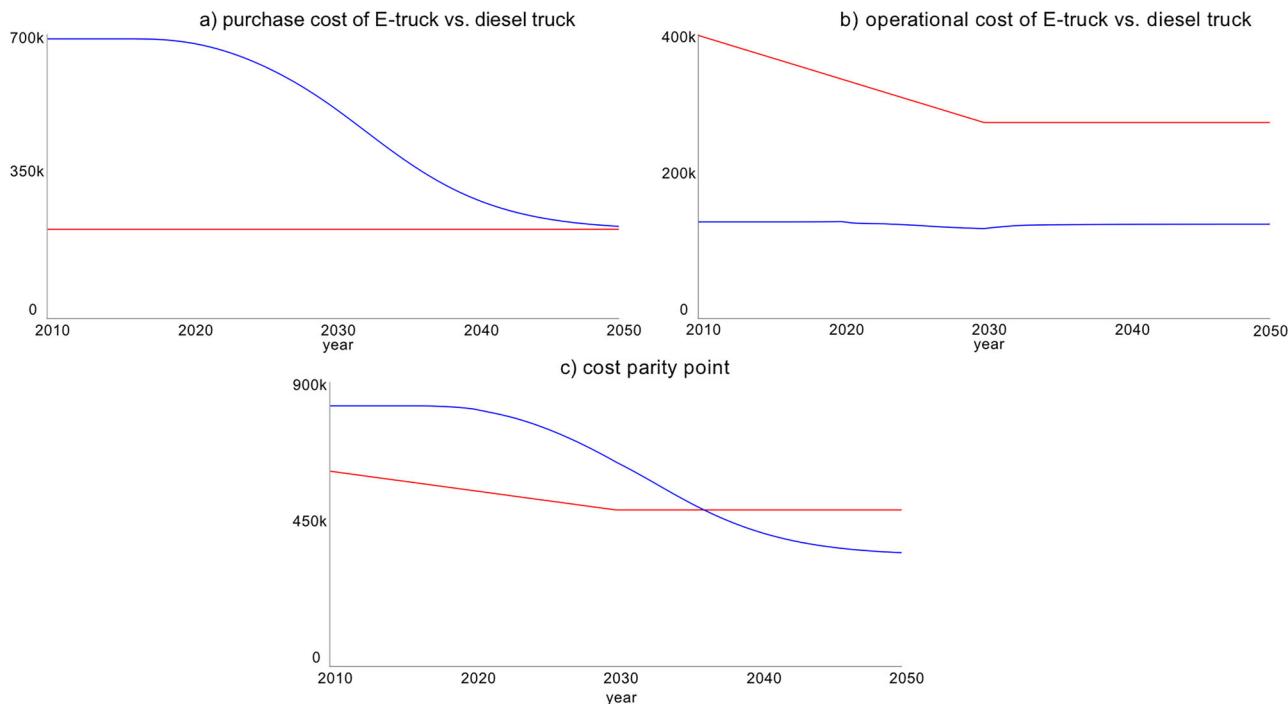


Fig. 5 | Cost parity point of E-trucks and diesel trucks. The figure compares the (a) purchase cost, (b) operational cost, and (c) total cost of E-trucks and diesel trucks over time.

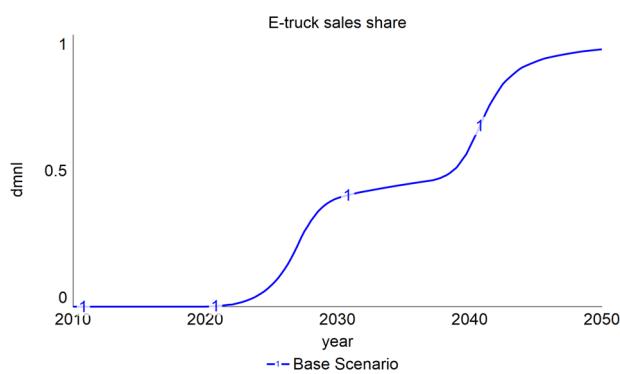


Fig. 6 | E-truck sales share. The figure highlights two S-shaped growth phases: the first phase (2025–2035) and the second phase (2035–2045).

four factors: the cost savings by using E-trucks, the availability of charging infrastructure, the technology maturity of E-trucks, and the emission ratio compared to the baseline. The figure reveals two connected S-shaped growth patterns, representing two phases of adoption: the first phase from 2025 to 2035 and the second from 2035 to 2045. The year of cost parity drives the transition from the first to the second phase. During the first phase, the cost parity point is not reached yet; thus, the cost does not drive E-truck sales, and the increase in sales is primarily driven by an increase in the availability of charging stations. Note that changes in cost can change the timing of cost parity, which in turn can influence sales dynamics. After reaching cost parity, during the second phase of adoption, E-truck sales are primarily driven by the decrease in the annual cost of E-trucks, driven by technology maturity.

What happens if we do not transition to E-trucks?

To assess the impact of not transitioning to E-trucks, we ran a simulation without them. Figure 7a shows that, in the no E-trucks scenario, transport cost per ton decreases until 2030 due to the improved fuel consumption rate of diesel trucks (based on Basma et al.⁶³) and then stabilises for the rest of the

simulation. However, when E-trucks are included, there's a temporary increase in cost per ton midway through the simulation, mainly driven by the initially high purchase costs of E-trucks. Ultimately, by improving the technology maturity of E-trucks, the annual cost of E-trucks is lower compared to diesel trucks (see Fig. 5 in the section "Base scenario results"). The lower annual cost, together with the higher E-truck fleet, leads to a lower cost per ton towards the end of the simulation.

As shown in Fig. 7b, transport efficiency stays relatively stable throughout the simulation in the no E-trucks scenario. However, when E-trucks are added, efficiency dips midway and then improves toward the end, but it doesn't reach the level seen in the no E-trucks scenario. Therefore, switching to E-trucks ultimately decreases transport efficiency due to the weight of the battery, the extra time required for detouring to charging stations, queuing, and charging, and the rebound effect of cost.

As Fig. 8 illustrates, switching to E-trucks can significantly lower the emission ratio compared to the baseline. Without E-trucks, emissions rise due to increasing freight demand. The spike in emissions in the year 2022 is linked to a change in Sweden's *Greenhouse Gas Reduction Mandate*⁷⁷. This mandate requires fuel suppliers to reduce emissions from diesel fuel by blending in biofuels. A government decision to significantly decrease the mandated biodiesel share led to a noticeable increase in emissions. The results of the base scenario-previous mandate illustrate the potential emission reduction if the mandate had not been changed.

Results of extreme condition and behaviour reproduction tests

As part of the model validation, as explained in the section "Model validation", eight extreme condition tests were conducted, summarised in this section and presented in detail in Supplementary Information 7. Results of extreme condition tests show that when E-truck adoption is disabled or delayed, diesel vehicles dominate the fleet, and long-term costs remain higher. Electrification generally results in lower cost per ton, higher freight demand, and improved sustainability outcomes, including reduced emissions and increased energy carrier efficiency, despite a slight decline in transport efficiency. Extreme scenarios, such as infinite E-truck lifetime or zero electricity cost, accelerate E-truck adoption and reduce system costs. However, rapid adoption can outpace infrastructure growth, leading to

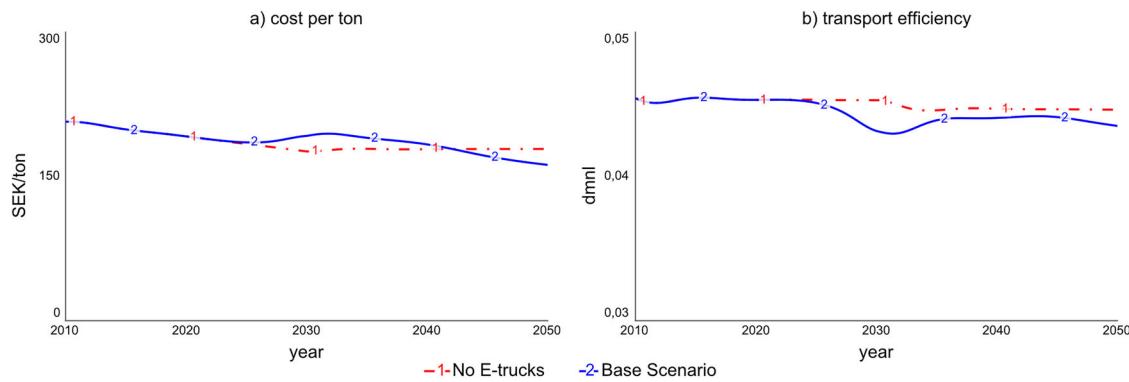


Fig. 7 | Comparison of base scenario vs. no E-trucks. The figure compares the base scenario with a no E-truck scenario on **a**) cost per ton and **b**) transport efficiency. Note that the y-axis in the transport efficiency figure does not start from zero, as the differences between the different policies would otherwise not be visible.

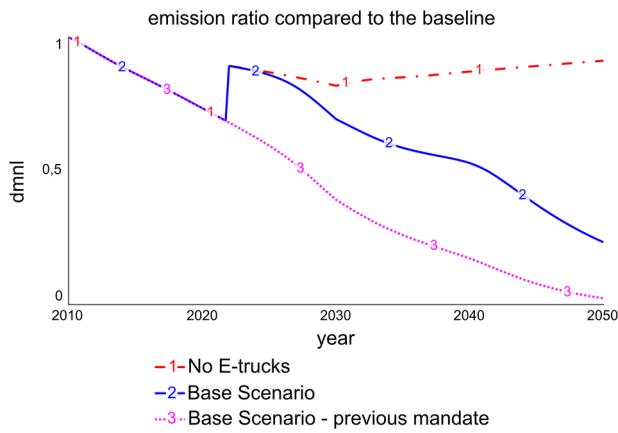


Fig. 8 | Comparison of emission ratio compared to the baseline across three scenarios. The figure presents the emission ratio relative to the 2010 baseline for the base scenario, a no E-trucks scenario, and the base scenario with the previous mandate.

reduced availability of charging infrastructure. Changes in parameters like the number of annual shifts per vehicle or share of empty kilometres significantly affect vehicle demand, vehicle utilisation, and fleet composition. Overall, the model responds as expected across these extreme condition tests, validating its internal consistency and highlighting the trade-offs relevant to policy analysis.

Moreover, several behaviour reproduction tests were conducted, comparing the model's output to actual data on transport work, distance driven, and the number of trucks⁶¹. These comparisons supported the calibration of parameters for which data was unavailable or limited and were reviewed with experts during the second round of interviews. Validation of the E-truck initial adoption proved more challenging due to limited data availability, as adoption is still in its early stages. Although the model does not exactly replicate the current E-truck fleet, experts noted that real-world figures are influenced by early-stage purchases for testing or branding purposes. To address this, based on expert recommendations, the focus was shifted to transport work by E-trucks. Expert feedback confirmed that this level of accuracy is sufficient for analysing the impact of electrification on transport efficiency. For more details about the behaviour reproduction, please refer to Supplementary Information 8.

Sensitivity analysis

To validate the model structure and to understand which variables have the most significant impact on the model results, we conducted a sensitivity analysis on 26 model parameters. In each test, we varied one parameter \pm 20% to understand each parameter's relative impact on the model's result. In

this section, two representative sensitivity analyses are discussed, while all 26 sensitivity runs can be found in Supplementary Information 9. Figure 9a, c show that the impact of the change in the price of electricity and diesel is only on the second phase of adoption. The cost does not drive the E-truck sales before the cost parity year, although it affects the timing of cost parity and can therefore influence sales dynamics. By comparing Fig. 9b – d, it can be seen how the diesel price increase has a higher magnitude than the electricity price increase. Moreover, Fig. 9b shows that a change in the price of electricity impacts the cost per ton, with a more significant impact towards the end of the adoption, as we have more E-trucks then. Similarly, Fig. 9d shows that a diesel price change impacts the cost per ton with a more significant impact at the start of the simulation, as we start in 2010 with a diesel truck share of 100%.

In addition, as explained in the section "Model Structure: simulation model", the E-truck sales share is determined by a weighted average of four factors: cost savings, availability of charging infrastructure, technology maturity, and emission ratio compared to the baseline. Due to the limited data available from large-scale E-truck adoption, these weights were estimated based on expert opinions and are uncertain. To address this uncertainty, a series of sensitivity analyses was conducted. The results show that doubling the weight of availability of charging infrastructure leads to a significantly higher adoption rate, while doubling the weight of cost savings slows down the adoption process. For further details, please refer to Supplementary Information 11.

Policy analysis

Based on the sensitivity analysis, we identified ten policy parameters with the most significant impact on the model's results. After several iterative meetings with experts, we selected four key policies, detailed below. All policies are implemented in the model from the year 2025, assuming future implementation.

- Carbon tax on price of diesel is imposed to account for the environmental costs associated with diesel use. This tax increases the overall price of diesel and is calculated based on the carbon intensity of diesel and the external cost of CO₂ (assumed to be 5 SEK per kg CO₂ based on Trafikverket⁷⁸). Introducing this tax would mean increasing the diesel price by 65%. In the model, the higher diesel cost shifts the cost parity year to an earlier year compared to the base scenario, making E-trucks more attractive than diesel trucks earlier than in the base scenario. Therefore, the influence of this policy is on Loop R3 - cost saving (Fig. 2). Additionally, the tax impacts the cost per ton, which is passed on to customers and leads to a change in their freight demand.
- Incentive on E-truck purchase provide a 20% subsidy on the purchase cost of E-trucks, making them more affordable. In the model, this incentive shifts the cost parity year to an earlier year and enhances the cost savings of using E-trucks, making E-trucks a more attractive option compared to diesel trucks. Similarly to the previous policy, the influence of this policy is on the loop R3 - cost saving (Fig. 2).

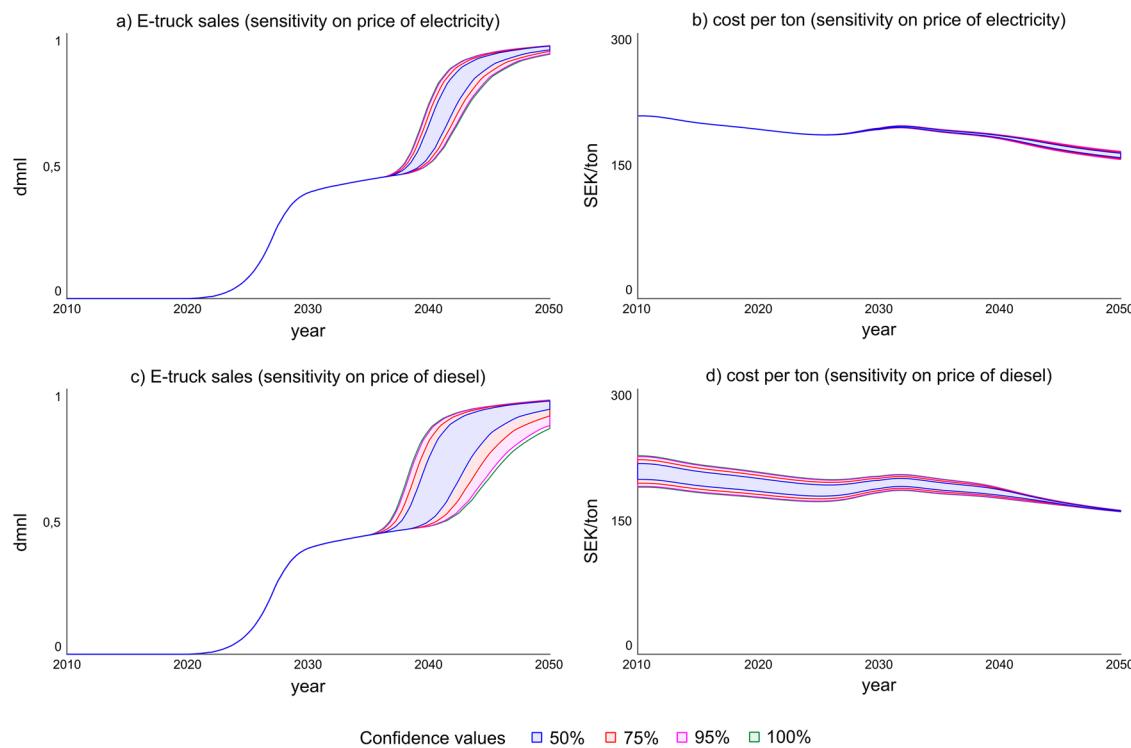


Fig. 9 | Results of sensitivity analysis. The figure shows the impact of a change of $\pm 20\%$ in the price of electricity per kWh on (a) E-truck sales share and (b) cost per ton, and the impact of a change of $\pm 20\%$ in the price of diesel per kWh on (c) E-truck sales share and (d) cost per ton.

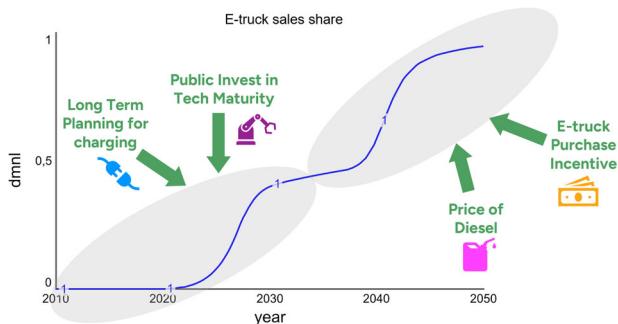


Fig. 10 | Design of the Combination Scenario. Infrastructure and maturity-related policies in the first phase of adoption and cost-related policies in the second phase.

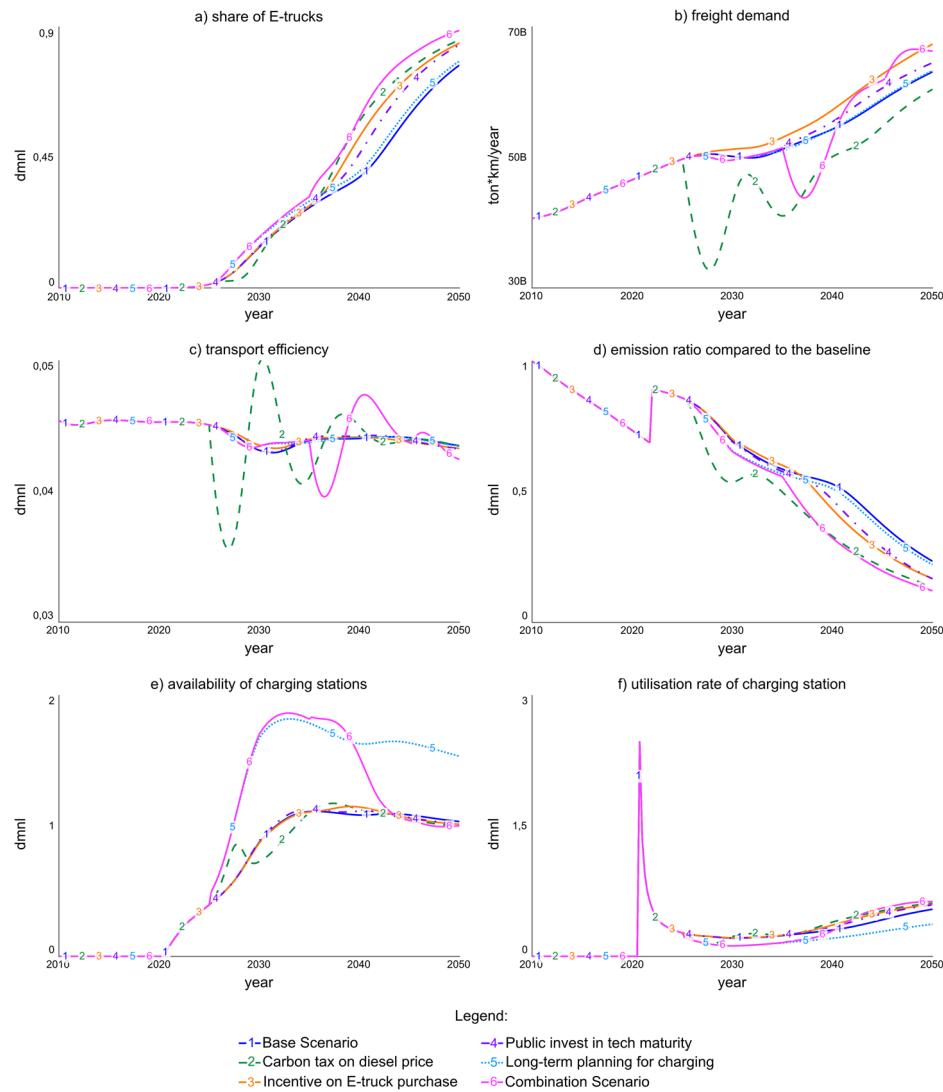
- Public investment in technology maturity is introduced as an additional driver. In the base scenario, only private investment is considered for increasing E-truck technology maturity. This policy assumes public sector investment to accelerate technology maturity. In the model, adding public investment speeds up E-truck technology maturity, leading to a decrease in the purchase cost of E-trucks. As technology matures, the costs associated with producing E-trucks decrease, resulting in lower prices for the trucks. Therefore, the influence of this policy is directly on loop R2 - tech maturity and indirectly on loop R3 - cost savings (Fig. 2).
- Long-term planning for charging is introduced to improve infrastructure development beyond the reactive approach in the base scenario, where charging station demand is based on the current E-truck sales. Within this policy, a prediction of future E-truck sales is added to determine the demand for charging stations and the construction of new ones. This approach emphasises long-term planning for the development of charging infrastructure. The influence of this policy is on the loop R4 - E-truck increase charging (Fig. 2).

The results of implementing these policies are shown in Fig. 11 and explained as follows.

Impact on E-truck share and emissions is illustrated in Fig. 11a, which shows the share of E-trucks under different policies. In the first phase of adoption (i.e., from 2025 to 2035), the “long-term planning for charging” policy results in the highest E-truck share, while the “carbon tax on diesel” produces the lowest share, even lower than the base scenario. This lower share with the “carbon tax on diesel” policy occurs because the tax increases diesel truck operating costs, leading to higher transport costs and a significant drop in freight demand, as shown in Fig. 11b. However, in the second phase of adoption (i.e., from 2035 to 2045), the “carbon tax on diesel” increases E-truck share, while “long-term planning for charging” has the most negligible impact. The different impacts in the first and second phases of adoption highlight the importance of charging infrastructure planning in the first phase and cost-focused policies in the second phase. In addition, Fig. 11d shows how the different policies impact the emission ratio compared to the baseline. The “carbon tax on diesel” policy achieves the most significant emission reductions. In contrast, the “incentive on E-truck purchase” policy shows higher emissions in the first phase of adoption compared to the base scenario. This increase occurs because the reduced E-truck purchase cost lowers transport costs, leading to higher freight demand, as seen in Fig. 11b. The increased freight demand results in more vehicles, including diesel trucks, contributing to higher emissions.

Impact on freight demand and transport efficiency is demonstrated in Fig. 11b, showing how freight demand changes under different policies and emphasising the importance of considering the cost-demand rebound effect when designing policies. The “carbon tax on diesel” policy significantly reduces freight demand due to the increase in transport costs. The oscillation observed in this policy is caused by a delay structure. As transport costs rise, freight demand decreases with a delay, which then signals a reduction in demand for trucks. This, with a delay, leads to a decrease in the total number of trucks, lowering total transport costs. Similarly, transport efficiency varies under different policies. As shown in Fig. 11c, the “carbon tax on diesel” policy causes the most fluctuation in transport efficiency, making it less desirable.

Fig. 11 | Results of policy analysis. The figure compares the base scenario with four individual policies (carbon tax on diesel price, incentive on E-truck purchase, public investment in technology maturity, and long-term planning for charging) and the Combination Scenario. It shows impacts on (a) E-truck market share, (b) freight demand, and efficiency variables including (c) transport efficiency, (d) emission ratio compared to the baseline, (e) charging station availability, and (f) charging station utilisation rate. Note that in (b) and (c) the *y*-axis does not start from zero, as the differences between the different policies would otherwise not be visible. The results for additional variables under the policy analysis are presented in Supplementary Information 12.



The trade-off between availability and utilisation rate of charging stations is shown in Fig. 11e, f. The “long-term planning for charging” policy results in the highest availability but lowest utilisation rates, while the “carbon tax on diesel” policy shows fluctuating patterns, ending with the lowest availability and highest utilisation rates. When charging stations are insufficiently available, their utilisation rates are high. However, as the availability of charging stations increases with new construction, the utilisation rate per station declines. A balance (trade-off) is needed to optimise both efficiency variables.

After investigating the impact of the single policies, we considered and explored the impact of different policies at different points in time. Based on the two phases of adoption (Fig. 6) and after several iterations during collaborative meetings with experts, we developed a Combination Scenario that simulates the following combination of policies, illustrated in Fig. 10:

- The *public investment in technology maturity* policy is active during the first phase of adoption. The effect of the technology maturity has many delays involved. For example, technology maturity increases (with a delay) the adoption of electrification, and the increase in technology maturity decreases the purchase cost and annual cost of E-trucks. Therefore, it is necessary to push technology maturity early on to see future benefits of E-truck adoption.
- The *long-term planning for charging* policy is active during the first phase of adoption since the availability of infrastructure mostly influences the first phase of adoption.

- The *carbon tax on price of diesel* policy is active during the second phase of adoption. This policy is relevant in the second phase as it affects the cost savings by using E-trucks.
- The *incentive on E-truck purchase* policy is active during the second phase of adoption. Similar to the previous policy, this policy is relevant in the second phase, as it affects the cost savings of using E-trucks.

The results of the Combination Scenario are depicted in Fig. 11, together with the other policies. As shown in Fig. 11a, the market share of E-trucks is higher in the Combination Scenario than all other policies at all time steps. Regarding the emission ratio compared to the baseline, Fig. 11d shows that the Combination Scenario is better than all other policies at all time steps, except for the *carbon tax on price of diesel* policy. The carbon tax is more efficient in reducing emissions if implemented in 2025 rather than only in the second phase of adoption. However, Fig. 11b shows how the Combination Scenario causes fewer oscillations in the freight demand compared to the carbon tax policy. These oscillations are attributed to the shock that the carbon tax policy brings to the cost of diesel trucks. The oscillations are of lower magnitude in the Combination Scenario, as the policy is implemented later (when there are fewer diesel trucks compared to 2025).

Discussion

In this study, we explored the impact of electrification on different kinds of road freight transport efficiencies and the dynamics between them. The

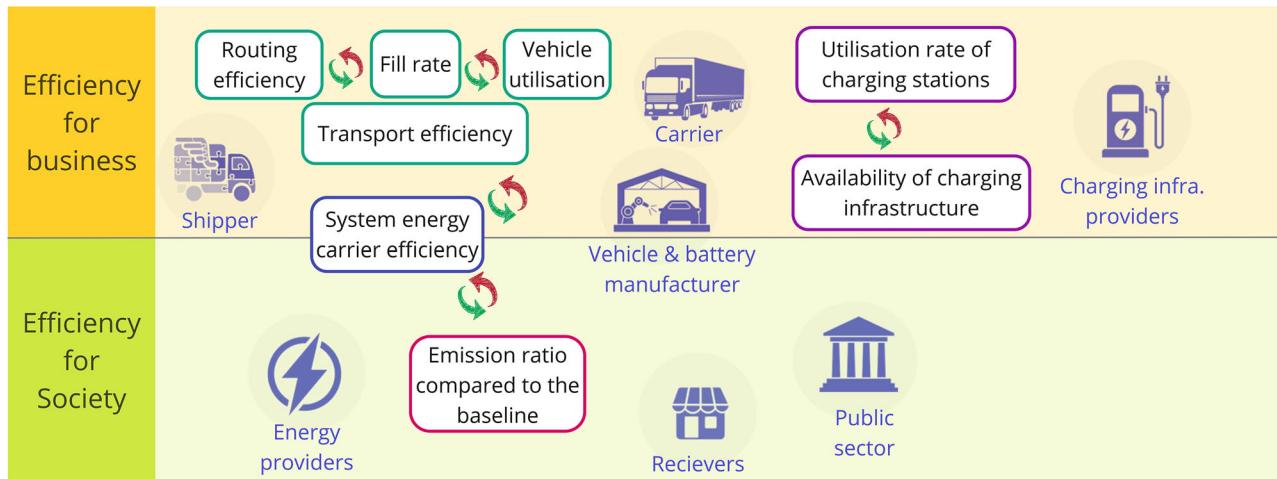


Fig. 12 | Different kinds of efficiencies. The figure presents the various efficiencies explored in the study, divided into efficiencies for business and for society, highlighting dynamics and relevant stakeholders. A summary of all efficiency variables modelled in the study is provided in Supplementary Information 6.

developed model is a dynamic model that includes rebound effects rather than a traditional static prediction model. This section addresses and discusses the research questions. We also delve into the methodological choices made during the study and conclude with a discussion on limitations, suggestions for future research and the main takeaways.

Trade-offs between different kinds of road freight transport efficiencies arise as electrification introduces new stakeholders, dynamics, and efficiency variables into the system. For example, charging infrastructure providers become key stakeholders who impact the availability of charging stations and are, in turn, affected by the utilisation rate of these stations. Figure 12 illustrates the different kinds of efficiencies explored in this study, categorised into efficiencies for business and for society. This figure is based on the insights from the literature^{8,16} and the results of interviews with experts. The figure also aims to depict the dynamics between these efficiencies and the involvement of various stakeholders.

This paper presents an SD model to answer the first research question, i.e., *how does electrification impact different kinds of efficiencies?* There is no definite answer, as electrification impacts different efficiencies in diverse ways, creating significant trade-offs to consider. For instance, Fig. 8 and Fig. 7b show that electrification can significantly reduce emissions, benefiting society, but it also decreases transport efficiency, impacting carriers. Moreover, Fig. 11e, f reveals that while increasing the availability of charging stations is beneficial for carriers, it can lower the utilisation rate of each station, affecting charging infrastructure providers. Thus, balancing and making trade-offs between different kinds of efficiencies is crucial.

From a cost perspective, as seen in Fig. 7a, electrification initially increases the cost per ton during the adoption phase. However, after reaching cost parity, the cost per ton ultimately decreases. Policymakers and decision-makers should acknowledge this worse-before-better behaviour and not be discouraged by an initial increase in cost per ton. This reduction in cost per ton can trigger a rebound effect, where lower costs drive higher demand. This rebound effect between cost and demand significantly influences the dynamics and final results of the model and must be considered carefully to avoid unintended consequences.

Policy discussion explores the impact of four policy interventions on the model to address the second research question, i.e., *how do policies impact the adoption of E-trucks and different kinds of efficiencies to achieve a more sustainable transport system?* The policies included are the following: *carbon tax on price of diesel*, *incentive on E-truck purchase*, *public investment in technology maturity*, and *long-term planning for charging*. Similar policies have been considered in the literature. For example, Raoofi et al.¹⁹ considered five policy levers, including charging and vehicle subsidies, technology maturity investments, electricity and diesel price changes. Moreover, Earl et al.⁷⁹ propose eight policies that are considered key to ensuring the

rapid and sustainable development of E-trucks in Europe, including fuel taxes, infrastructure standards, and funds for battery manufacturing. However, Earl et al.⁷⁹ base their results on a static analysis, not considering change over time and dynamic complexity. McNeil et al.⁸⁰ report a surprisingly high impact of tax credits and incentives to support electrification, together with the construction of infrastructure in the USA. These results are in accordance with our results, as they identify and test similar policies.

As shown in Fig. 6, two phases of adoption are identified. The year of cost parity divides the two phases. The cost parity point is explored by various authors in the literature (e.g., refs. 19,57,63,64), and it depends on battery and truck size, distance driven, and application^{81,82}. In our model, we aggregate all trucks heavier than 3.5 tonnes; therefore, the cost parity point is also aggregated. During the first phase, the increase in sales is primarily driven by an increase in the availability of charging stations. Therefore, policies that improve the availability of charging stations during the first phase can boost E-truck adoption. After reaching cost parity, during the second phase of adoption, E-truck sales are primarily driven by the decrease in the annual cost of E-trucks. Therefore, policies that decrease the annual cost during the second phase, such as energy carrier pricing, boost the adoption. It should be noted that changes in cost can affect the timing of cost parity, which in turn can influence sales dynamics. The importance of cost and charging infrastructure is also highlighted by McNeil et al.⁸⁰. In addition, Raoofi et al.¹⁹ identified charging infrastructure as a key enabler of adoption. This aligns with our findings, which show that infrastructure-focused policies significantly drive adoption in the first phase, creating a ripple effect that extends through the end of the simulation.

The knowledge gained from the analysis of the single policies described in the section “Policy analysis” enables us to combine policies to achieve effective impacts on the system regarding both E-truck adoption and transport efficiencies in the Combination Scenario. When taking the public sector perspective, one potential policy caveat is to balance incentives and taxes. For example, the *public investment in technology maturity* policy is an incentive that costs money to the public sector. In contrast, the *carbon tax on price of diesel* policy is a tax that brings money to the public sector. Figure 13 shows the Total Public Sector Revenue, which is calculated as a stock (accumulation) by considering both the incentives (seen as an outflow to the revenue) and taxes (seen as an inflow to the revenue). The *long-term planning for charging* policy is seen more as a regulation (without direct taxes or incentives). The figure shows that the *carbon tax on price of diesel* policy has a high revenue, while the *incentive on E-truck purchase* brings a high expense to the public sector. The *public investment in technology maturity* policy brings an expense to the public sector, but much less than the expenses in *incentive on E-truck purchase* policy. It is clear how the policies with high expenses for the public sector could not be economically

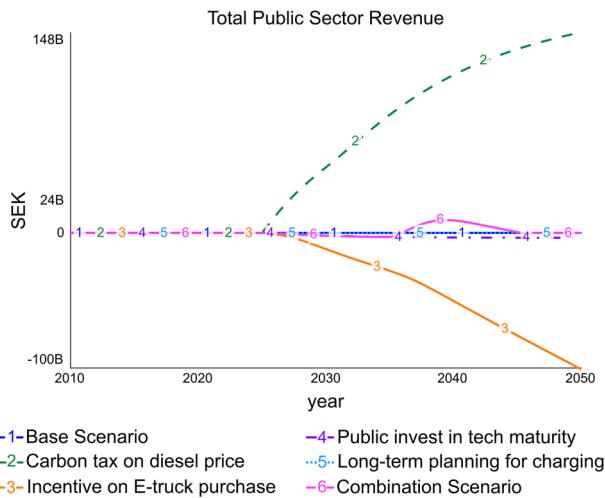


Fig. 13 | Cumulative change in Total Public Sector Revenue in the Base Scenario and under different policies. The Combination Scenario is the only scenario where the revenue is zero at the end of the policy period (2045). A zoomed-in version of this figure is provided in Supplementary Information 12.

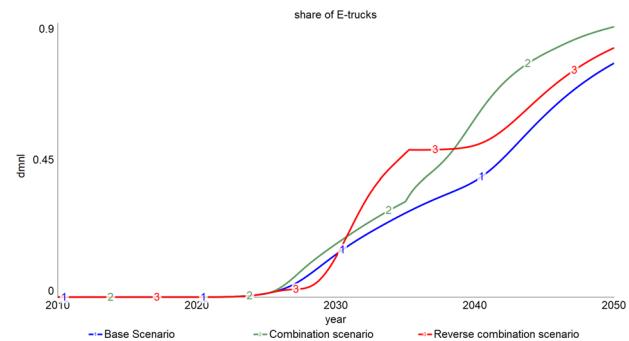


Fig. 14 | Share of E-trucks across scenarios. The figure shows the share of E-trucks in the Base Scenario, Combination Scenario, and Reverse Combination Scenario.

viable in the long run since they penalise either the carriers and their customers (with the carbon tax) or the public sector (with the incentives). Therefore, a balance should be sought in the Total Public Sector Revenue. This balance could be achieved when combining the policies in the Combination Scenario. Figure 13 shows that the revenue in the Combination Scenario is negative during the first phase of the adoption and positive during the second phase, becoming zero at the end of the policy period. Therefore, in the Combination Scenario, E-truck adoption can be increased while maintaining a reasonable balance in the Total Public Sector Revenue. This highlights the importance of implementing effective policies that accelerate E-truck adoption while achieving high gains per unit of public expenditure, thereby offering better value for government action.

Evaluating policy recommendations and the consequences of model assumptions, a *Combination Scenario* was developed through discussions with our expert group. However, in reality, there are numerous potential policy interventions, both in terms of the policy types and the implementation time. To support broader experimentation, we built an interactive interface based on the simulation model (<https://exchange.iseesystems.com/public/treff-model/interface>), allowing decision-makers to test different policy combinations and observe real-time results.

In the *Combination Scenario*, we recommend implementing cost-related policies during the second phase of adoption (after the cost parity point) and infrastructure-related policies during the first phase. However, applying cost-related policies after reaching cost parity may appear counterintuitive. Our results suggest that to further accelerate adoption, continuing to reduce the cost of E-trucks, even beyond the parity point, can be an effective policy intervention.

To explore this further, we tested a *Reverse Combination Scenario*, in which we swap the timing of policy interventions, applying cost-related policies in the first phase and infrastructure-related policies in the second phase. As shown in Fig. 14, the *Combination Scenario* results in a higher share of E-trucks by the end of the simulation compared to the *Reverse Combination Scenario*. The latter shows a sharp drop in sales in the mid-2030s, when cost-related policies are withdrawn and greater fluctuations in transport efficiency occur, which are undesirable for manufacturers, freight operators, and other stakeholders relying on system stability. Further details are provided in Supplementary Information 13.

In addition, regarding the influence of cost savings on E-truck adoption, the Base Scenario, based on the discussion with our experts, assumes that prior to reaching cost parity, adoption is driven by other factors (charging infrastructure availability, technology maturity, and emission

ratio compared to the baseline). Once cost parity is achieved, cost begins to contribute to adoption decisions. However, we tested an alternative assumption in which freight companies consider cost savings as a factor from the beginning of the adoption, even before cost parity is achieved. Under this alternative scenario, the overall two S-shaped patterns of E-truck sales share remain, but the second growth phase shifts to the left, indicating earlier uptake. Further details are provided in Supplementary Information 14.

Methodological discussion is presented as follows. SD is used in this paper to zoom out and have a broader perspective on the concept of efficiency and the impacts of electrification. The model was grounded in the scientific literature (see the section “Model Structure: simulation model”) while also being shaped through a participatory process. These two approaches complemented one another: the literature provided a scientific foundation, while the participatory process ensured relevance to real-world conditions and improved the model’s face validity⁸³. By combining these approaches, the model benefits from both academic rigour and stakeholder relevance, thereby strengthening its ability to support policy analysis.

Building on participatory modelling approaches commonly used in SD research^{84,85}, we actively engaged stakeholders from industry, the public sector, and academia to understand their decision-making mechanisms and identify key variables. For example, we examined how carriers weigh the trade-offs between adopting electric versus diesel trucks, how truck manufacturers make decisions to increase investment in vehicle technology development, and how policymakers evaluate investment strategies to support the transition. Once the initial model was developed, we returned to experts to validate the results and ensure the model’s behaviour aligned with their expectations. Using an interactive interface built as part of the study, experts were able to directly test the model by simulating different policies and decisions. We conducted several “if-then” analyses, such as, “If the diesel price decreases, what behaviour would you expect from the model?” When model behaviour did not align with expert expectations, we used sensitivity analysis and further testing to explore the underlying structure and refine the model accordingly.

These engagements, carried out through interviews, workshops, and expert meetings (see Supplementary Information 2), were critical in capturing experts’ mental models and ensuring that the model is relevant to real-world challenges. Moreover, participants and experts reported that the study helped them to understand the system’s dynamics using a new method. These findings and results align with the participatory approach in SD modelling highlighted by refs. 46,86,87.

Apart from using the method as a participatory approach, the model itself contributes to the literature. The model can be used by policymakers in Sweden to understand the impacts of various policies. Moreover, the model can be adapted to represent the road freight transport system in other countries by changing the input data and confirming that the same dynamics are valid in the new context. Therefore, this paper provides a tool that can be used in different case studies to understand the impacts of electrification on road freight transport efficiency and how various policies

impact the adoption of E-trucks and efficiency. Moreover, the SD model in this paper can be used for dynamic policymaking, as it allows us to consider the dynamic impacts of different decisions and policies. Therefore, using SD models significantly contributes to decision-makers and policymakers in the field.

Other modelling methods could be used to tackle the problem described in this paper. For example, agent-based models are a powerful tool for solving complex questions and have been extensively used in transport planning⁸⁸. Köhler et al.⁸⁴ review the application of modelling methodologies to explain the dynamics of transitions and identify many possible methods, including evolutionary economics models, SD models, agent-based models, and socio-ecological systems models. Mercure et al.⁸⁹ highlight that models to simulate sustainability policymaking should include the feedback structures caused by human behaviour and propose an alternative modelling approach based on complexity dynamics and agent heterogeneity. We chose SD, as it allowed us to explore the dynamics of the transition while keeping a holistic perspective and focus on the system-level effects rather than the details of the technological shift to electrification and bridging a gap between detailed technical models and qualitative policy studies.

Limitations and future studies are presented as follows. The initial efforts to define efficiencies have proven that there are many different kinds of efficiencies, and covering all of them could be challenging. Each stakeholder group has its own different definitions and understandings of efficiencies, making it hard to generalise efficiency as a concept on a system level. Future studies could build on this by incorporating additional definitions of efficiency from other stakeholder perspectives. In particular, examining investment efficiency from the public sector perspective would be beneficial. Although we have touched on this aspect by considering Public Sector Revenue in the policy discussion, future research could undertake a more detailed and concrete analysis to assess the efficiency of different policy interventions.

The study focuses on the competition between E-trucks and diesel trucks, excluding alternative fuels such as biofuels and hydrogen. It also aggregates heavy trucks (over 3.5 tonnes) into a single category. For future research, it would be beneficial to explore the dynamics of other alternative fuels and to segment the vehicle fleet by weight class for more detailed analysis. Moreover, the model also considers charging stations as the main charging solution, leaving out other charging strategies such as Electric Road Systems and battery swapping, in line with EU-level priorities (e.g., AFIR) and Sweden's national electrification plan⁵⁸. Charging stations are also treated in aggregate, without differentiating between depot, highway, or destination charging. The focus is on how the availability of charging stations influences E-truck adoption, rather than the dynamics between specific charging choices. However, incorporating distinct charging strategies would be a valuable direction for future model development. In addition, the impact of emerging technologies such as autonomous driving and vehicle-to-grid (V2G) was not considered in this model but could be explored in future research.

The model is based on the Swedish market and government, with validation from experts in Sweden. While the data used is specific to Sweden, the model can be generalised by adjusting its structures and input parameters. Future research could compare the model's results across different countries with varying policy schemes. Additionally, expert knowledge and judgement were used during model development where necessary, which introduces potential limitations due to the bounded nature of expert perspectives, even among domain experts. Future work could involve a broader range of experts and compare outcomes across stakeholder views.

The model considers four factors influencing E-truck adoption: cost savings by using E-trucks, the availability of charging infrastructure, the technology maturity of E-trucks, and the emission ratio compared to the baseline. Future studies could explore additional factors, including those that might negatively impact adoption, such as range anxiety for drivers or uncertainties related to energy prices.

One of the contributions of this model is the consideration of the rebound effect of the change of cost per ton on the freight demand.

However, the elasticity is considered a constant. It would be more realistic to express the elasticity as a function of the change in price. For example, elasticity in response to a small price variation is likely to differ from that under a large price variation. For instance, Fig. 11b shows a great reduction of demand when the carbon tax policy is implemented starting in 2025. This change could be unrealistic since the change in demand would be lower the more the price deviates from its past behaviour. We believe, therefore, that making the elasticity endogenous is an interesting avenue for future work, while in this paper it is considered out of scope.

Moreover, the model does not currently account for regional variation, fuel and technological diversity. It also does not explicitly represent the heterogeneity in the decision-making of the different fleet operators, such as the difference in risk tolerance, fleet renewal strategies, or responsiveness to policy incentives, which could influence adoption trajectories. While these aspects were discussed qualitatively during the participatory process, they are not entirely formalised in the current model structure. Future work could introduce behavioural heterogeneity and complement this model with more disaggregated, spatially explicit models to enhance both behavioural and geographic resolution.

Finally, the transition to E-trucks involves significant uncertainties, including how electrification will impact various variables, the ripple effects of these changes, and how policymakers will respond. While a long simulation time is necessary to understand the dynamics of the system in the long run, it also introduces greater uncertainty about input parameters. Future studies should account for these uncertainties, employing techniques like the Decision Making under Deep Uncertainty approach to better manage variability in input parameters and model assumptions (see e.g., ref. 90).

Conclusions

This paper explores the impact of electrification on road freight transport efficiency, considering efficiency as a complex concept with the involvement of various stakeholders. Electrification introduces new stakeholders, dynamics, and efficiency variables, adding further complexity to the system. To address this complexity and understand the dynamics of the system, this paper utilises System Dynamics (SD) modelling. This method allows for exploring the interactions between different efficiencies and stakeholders and understanding how electrification affects the system. Our model distinguishes between different kinds of efficiencies and the impact of electrification, with several dynamics between them.

The key takeaways of the paper can be summarised as follows:

- There are trade-offs between different kinds of efficiencies. For example, while electrification reduces emissions, benefiting society, it also decreases transport efficiency, impacting carriers. Moreover, investing in and building more charging stations increases availability, making it more convenient for carriers to access charging stations. However, greater availability leads to lower utilisation rates for each station, which affects charging infrastructure providers. Therefore, it is essential to achieve a balance between these different kinds of efficiencies.
- Electrification increases the cost per ton temporarily during adoption, but after reaching cost parity, it ultimately lowers the cost per ton, making the transition to E-trucks cost-effective in the long run. However, this decrease in cost per ton can trigger a rebound effect, where lower costs drive higher demand, potentially leading to externalities such as emissions and congestion. This rebound effect significantly influences the dynamics and results of the model, so it must be carefully considered to prevent unintended consequences.
- The model results indicate two phases of E-truck adoption. In the first phase (2025-2035), policies focused on expanding charging infrastructure significantly impact adoption. In the second phase (2035-2045), cost-focused policies become more influential. Given the delays inherent in the system, a long-term perspective is essential to accelerate E-truck adoption. For example, public investment in technology maturity should be implemented early to achieve the desired outcomes. Based on these insights, we developed a *Combination Scenario* that

boosts E-truck adoption while simultaneously reducing public expenses (balancing financial incentives against tax revenues). This policy analysis underscores the crucial role of policymakers in the system and the importance of making decisions at the right time and in the right place.

The main contribution of this paper is the development of a dynamic and feedback-rich model that sheds light on how electrification impacts freight transport efficiency while highlighting the critical role of planning and policymaking in successful electrification and improved efficiency variables. The model offers a system-level perspective that goes beyond isolated efficiency metrics, linking E-truck adoption, business and operational efficiencies with societal and environmental efficiencies in an integrated, dynamic framework. By using a participatory process with experts from industry, the public sector and academia, we ensure that the model's logic and results reflect both empirical data and expert knowledge, allowing for sound policy analysis. Moreover, our policy analysis offers insights into how policymakers can leverage such a model to make informed decisions at the right time and in the right place. This paper provides valuable knowledge to Swedish policymakers and those in similar contexts and can guide them towards targeted interventions that help navigate the transition to a sustainable road freight transport system.

Data availability

The model documentation and data sources of this study are publicly available and can be accessed at https://github.com/ZeinabRaooft/TrEff_Stella_Model.

Code availability

The SD simulation model utilising Stella Architect version 3.2.1 is publicly available and can be accessed at https://github.com/ZeinabRaooft/TrEff_Stella_Model. An online interactive version is also available, allowing users to engage with the model without requiring Stella software. Access the interface here: <https://exchange.iseesystems.com/public/treff-model/interface>.

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Author contributions

ZR: conceptualisation, investigation, methodology, software, validation, visualisation, writing – original draft, writing – review and editing. CA: conceptualisation, investigation, methodology, software, validation, visualisation, writing – original draft, writing – review and editing. RM: methodology, software, supervision, writing – review and editing. ZR & CA should be considered as equally first authors.

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Competing interests

The authors declare no competing interests.

Additional information

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