

Article

Electric Vehicle Adoption in Urban Logistics: A Nonlinear Interaction and Scenario Analysis in the Case of Lithuania

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Abstract

This study investigates the key drivers and barriers influencing the adoption of electric vehicles (EVs) in urban freight logistics, using Lithuania as a case study. An integrated methodological framework combining Delphi, Fuzzy logic, DEMATEL, and System Dynamics is applied to identify critical factors and analyse their interdependencies. Four main drivers are identified: infrastructure, acquisition costs, technological development, and policy measures. Expert evaluations are transformed into fuzzy values to quantify factor importance, which are then incorporated into a dynamic simulation model to assess EV adoption and CO₂ emission trends. In addition to baseline scenarios, extreme scenario analysis is conducted to evaluate system sensitivity to economic, technological, and policy changes. The results reveal strong nonlinear relationships between factors and highlight the importance of their balanced development. The findings suggest that rapid EV adoption in urban logistics requires a coordinated approach integrating infrastructure expansion, financial incentives, technological progress, and policy support. The study provides practical insights for policymakers and logistics companies aiming to accelerate sustainable urban transport transitions.

Keywords: electric transport; freight logistics; sustainability; Delphi method; CO₂ emissions; system dynamics

1. Introduction

Urban freight logistics is one of the largest sources of strain on urban transportation systems, contributing to air pollution, noise, traffic congestion, and energy inefficiency. Traditional internal combustion engine-powered trucks generate significant CO₂ emissions, which is why many countries are increasingly focusing on integrating electric vehicles (EVs) into urban logistics systems. In Lithuania, as in other European countries, the adoption of EVs in freight transport is still in its early stages, and companies face complex challenges involving infrastructure development, investment needs, technological solutions, and political/regulatory factors. The literature emphasizes that the evaluation of EV implementation decisions is a complex process. Previous studies have primarily focused on technological parameters, economic calculations, or the effectiveness of policy measures in individual cities. However, there is a lack of systematic methods that integrate expert opinions and allow for the quantitative assessment of key factors and their interactions within the context of urban logistics in Lithuania. To address this gap, this article applies the Delphi method to identify and evaluate expert opinions, and the resulting weights are integrated into a system dynamics model that allows for the simulation of the impact of factors limiting



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EV deployment and several EV deployment scenarios for urban freight transport. In this way, the model makes it possible not only to identify critical factors but also to forecast the impact of different strategies, taking into account infrastructure, investments, technological advances, and policy measures.

The aim of this article is to identify the key factors determining the development of electric vehicles in urban freight logistics in Lithuania and to quantitatively assess their impact on the logistics system, sustainability, and CO₂ emission reduction, using expert assessment (the Delphi method) and system dynamics modelling. The study primarily aims to identify the most important factors determining the adoption of electric vehicles in urban freight logistics, and their significance and influence are assessed using the Delphi–Fuzzy method to reduce the uncertainty of expert assessment. The insights obtained from experts are integrated into a system dynamics model, allowing for the simulation of various electric vehicle deployment scenarios and the assessment of the logistics system’s resilience to external shocks. Based on the model’s results, recommendations are formulated for decision-makers regarding electric vehicle deployment strategies and the transformation of the logistics system. To evaluate different development possibilities, several scenarios will be simulated to assess the system’s resilience to external shocks, in which expert assessments are used to determine the values of factors and their impact on the growth rate of electric vehicles and the transformation of the logistics system. Although most previous studies have focused on the analysis of baseline scenarios [1–6], increasing attention is being paid to assessing the resilience of systems in the face of uncertainty. Therefore, in this study, in addition to conventional scenarios, an analysis of extreme scenarios is applied, allowing for the assessment of system behaviour under significant external changes. This study contributes to the existing literature by developing an integrated “Delphi-Fuzzy DEMATEL-System Dynamics” methodology for analysing the implementation of electric vehicles in urban freight logistics. Unlike previous studies, which focused on individual factors, this study examines the nonlinear interactions among key factors and evaluates the system’s behaviour in both baseline and extreme scenarios. Furthermore, the study presents empirical insights based on the Lithuanian context that can be applied to similar emerging urban logistics systems.

2. Materials and Methods

2.1. Theoretical Aspects of the Implementation of Electric Vehicles in Urban Freight Logistics and Sustainability Solutions

Rapid urbanization and the growing volume of e-commerce are making urban freight logistics one of the most critical areas where the goals of economic efficiency, environmental protection, and social sustainability converge. As traffic volumes increase, so do the associated problems—traffic congestion, air pollution, and noise—leading to a growing focus on finding innovative and sustainable solutions. In this context, the adoption of electric vehicles stands out as one of the most promising avenues, capable of significantly contributing to the transformation of urban logistics systems. However, the technological transition to electric transport alone is not sufficient to achieve long-term sustainability. It is necessary to comprehensively evaluate different implementation alternatives and their impact on urban infrastructure, logistics processes, and stakeholder behaviour. Therefore, this section analyses alternatives for the deployment of electric vehicles and related sustainability solutions in urban freight logistics, emphasizing an integrated approach that encompasses technological, economic, and social aspects. In a study of freight logistics in Casablanca conducted by Amrani et al. [7], the impact of urban traffic flows on congestion, emissions, and economic losses was effectively modelled using large-scale simulations, which allowed for a quantitative assessment of the effectiveness of various logistics scenar-

ios. Applying this methodology to the Lithuanian context makes it possible to forecast how different electric transport deployment strategies—a fully electric fleet, partial integration, or a mixed model—would affect traffic conditions in the city center, pollution levels, and delivery efficiency. Furthermore, by combining simulation models with expert assessments, it is possible to identify the optimal alternative that would minimize CO₂ emissions and economic losses while ensuring efficient freight logistics and a socially acceptable urban environment [7]. Research also shows that technological solutions alone do not ensure a sustainable transformation of urban freight logistics if they are not properly integrated into business models and operational processes. Buijs [8] notes that many innovative solutions, although technically ready for implementation, face significant challenges in transitioning from pilot projects to widely adopted business models capable of competing with “business as usual” practices and ensuring long-term impact. A case study of the ULaaDS project in Bremen, Mechelen, and Groningen reveals that sustainable urban freight transport solutions must be designed as integrated systems that combine technological, business, and regulatory aspects in order to achieve commercial viability and economies of scale. Furthermore, it is emphasized that close cooperation between the private sector and public institutions is essential for innovative solutions to be successfully integrated into existing systems and scaled up to large-scale logistics networks [8]. Studies on sustainable urban logistics highlight that the optimization of micro-hub networks and efficient route planning are among the most important factors in reducing CO₂ emissions and traffic congestion.

Castillo et al. [9], using routing algorithms, optimized the layout of intermodal micro-hubs and freight distribution in the city of Barcelona, based on real-world data and multi-objective optimization that accounted for both operational and routing costs. The results showed that out of 1057 potential infrastructure points, only about 61 micro-hubs are sufficient to efficiently handle high freight volumes, thereby reducing the total number of kilometres travelled, CO₂ emissions, and delivery times. Furthermore, this system promotes intermodality by integrating low-emission vehicles, such as electric vans and cargo bikes, thereby contributing to the achievement of EU transport policy goals. Such solutions not only reduce environmental impact but also demonstrate that properly designed micro-hub networks can become a key strategy for achieving sustainable urban logistics [9]. Research shows that the electrification of urban freight transport and regulatory measures such as low-emission zones and financial incentive schemes can significantly reduce CO₂ emissions in European cities. However, their effectiveness strongly depends on the level of infrastructure development and market acceptance. Chen et al. emphasize that technological solutions alone are not sufficient—a comprehensive political and social approach to urban logistics decarbonization is required, encompassing both infrastructure planning and changes in user behaviour [10]. Studies examining the implementation of eco-logistics solutions in cities indicate that not only technological solutions but also public awareness and citizen acceptance play an important role. A study conducted in the city of Szczecin showed that residents are well informed about eco-logistics measures and generally support initiatives such as shared parcel pickup points, electric scooters, and electric and hybrid vehicles. Respondents associated these solutions with improved air quality, reduced noise, and increased mobility efficiency. The results confirm that public acceptance is a key factor in implementing sustainable urban logistics systems, as even technologically advanced solutions may be less effective without societal support. However, the study also highlights practical challenges, such as limited impact in less urbanized areas and conflicts between different transport modes, which may contribute to congestion [11]. Meanwhile, in the European urban context, sustainable urban logistics initiatives are becoming increasingly important in addressing transport-related CO₂ emissions, air pollution, noise, and traffic congestion. Recent studies show that urban logistics is one of the main sources of

urban emissions; therefore, many cities are implementing electric vehicles, low-emission zones, and alternative last-mile delivery models. Drop and Chelstowska emphasize that the effective implementation of sustainable logistics solutions requires an integrated approach that includes not only technological aspects but also social and political factors, including public participation and institutional cooperation. Galambos et al. [12], having reviewed projects from the past decade, identified and systematized various sustainable logistics initiatives in Europe, encompassing both infrastructure changes and the improvement of operational strategies. Their analysis provides not only a comprehensive overview of the initiatives but also practical recommendations for decision-makers, emphasizing that effective measures must be integrated into urban planning and aligned with the specific characteristics of local logistics. The city's spatial structure and urban morphology also have a direct impact on the sustainability and efficiency of freight logistics.

Galkin et al. [13] found that factors such as urban density, street network structure, and the layout of central zones determine logistics indicators, including kilometers travelled, delivery time, and emissions. Compact, high-density cities create more favourable conditions for shorter routes and lower emissions, whereas sprawling areas pose challenges for sustainable planning. This indicates that logistics solutions must be coordinated with urban planning to achieve maximum efficiency and minimal environmental impact [13]. According to Kumar, Goel, and Tiwari [14], the deployment of electric freight vehicles (EFVs) in cities is constrained by various complex barriers. Kumar, Goel, and Tiwari, using multi-criteria analysis methods (Fuzzy-Delphi, DEMATEL, and ISM), identified key challenges, including insufficient government incentives, unregulated market conditions, high operating costs, and a long payback period. They also highlighted issues related to limited charging infrastructure, an immature resale market, and a lack of specialized repair centers, which hinder the integration of EFVs into logistics systems [14]. Future urban logistics scenarios may develop in different directions, ranging from socially oriented sustainable models to technology-based autonomous systems. Tadić et al. [15] emphasize that decision-making in this field requires multi-criteria methods that allow for the reconciliation of efficiency, sustainability, and social acceptability [15]. Literature reviews also indicate that sustainability assessment methodologies in urban logistics remain fragmented. Aung et al. [16] highlight the need to develop integrated assessment systems that encompass transportation, infrastructure, and social and economic aspects to improve the rationale for decision-making [16]. Studies further emphasize that the integration of DI with electric vehicles can significantly improve last-mile delivery.

Ferreira and Esperança [17] found in the case of Lisbon that such integration reduced delivery times, energy costs, and emissions, while improving operational efficiency [17]. Not only technological advantages but also urban planning aspects are important when integrating light electric functional vehicles (LEFVs) into urban logistics systems. Studies examining the use of LEFVs in zero-emission zones—areas with strict pollution restrictions—show that the use of LEFVs can improve traffic conditions, reduce pollution, and even enhance mobility for other modes of transport, such as bicycles or pedestrians. However, the lack of space for parking, charging, and loading/unloading zones poses additional challenges, so logistics flow planning must be integrated with urban infrastructure and the management and regulation of urban spaces [18]. Furthermore, the development of LEFVs contributes to the creation of a broader sustainable logistics system that promotes the reduction in not only CO₂ emissions but also noise and congestion, while improving the quality of urban life and environmental indicators. Bibliometric studies show that scientific research in this field is growing rapidly, and the use of LEFVs is evaluated both in terms of technical and economic assumptions and in terms of urban space and policy aspects, although the latter still require deeper analysis [2]. However,

while LEFVs have significant potential to transform urban freight logistics, overcoming the barriers to their deployment still depends on various factors, including initial investment, the development of charging infrastructure, the creation of policy incentives, and the improvement of local regulatory frameworks, which, together with AI solutions, can pave the way for more sustainable urban logistics. Efficient last-mile delivery can only be achieved by aligning technological, organizational, and public sector instruments that allow for the holistic—rather than fragmented—integration of LEFVs solutions. The growing intensity of e-commerce demand necessitates the implementation of efficient and sustainable last-mile logistics strategies, in which electric vehicles become the primary solution. Sustainable freight delivery strategies that combine the use of EVs, optimized routes, and advanced charging infrastructure systems not only reduce carbon dioxide emissions but also improve operational reliability, reduce noise pollution and transportation costs, ensuring smooth delivery operations in the intensifying e-commerce market [19]. Furthermore, recent studies emphasize that the deployment of electric freight vehicles must be coordinated with advanced route optimization algorithms, charging infrastructure planning, and urban transport policy, as only such an integrated strategy allows for maximum energy savings and logistical efficiency, the deployment of electric freight vehicles must be coordinated with advanced route optimization algorithms and charging infrastructure planning in the face of uncertainty, as integrated route planning and charging models significantly improve operational efficiency and system feasibility in real-world logistics networks [20]. Modern models also account for uncertainties regarding demand, seasonality, and network load, so EV deployment strategies are becoming increasingly adaptable to real-world urban operations and can be flexibly applied in the contexts of different cities. In this way, the integration of electric vehicles into urban freight logistics becomes not only a technological but also a strategic solution, helping to align economic, operational, and environmental goals in a rapidly growing e-commerce environment. The scientific literature on the integration of electric vehicles into logistics systems and freight transport is increasingly shifting toward practical and operational solutions. The newly published works go beyond general arguments for sustainability—they specifically examine logistics infrastructure planning, regional trials, and strategic decisions that have a direct impact on urban freight logistics and truck electrification [21]. One of the key research topics is the planning of charging infrastructure locations and capacity for the integration of a large-scale electric truck fleet into freight logistics.

Another important research study addresses the evaluation of practical testing and operations in the context of urban logistics. The Swedish National Road and Transport Research Institute (VTI) conducted a pilot experiment in which an electric minibus was used for urban logistics operations (food and medicine delivery) under the same schedule and load conditions as its diesel counterpart. The study results showed that the EV not only met operational requirements (covering 70–90 km daily) but also consumed only about 30% of its battery capacity in daily operation, leaving potential for longer distances. This indicates that even with current battery technologies, EVs can effectively serve urban freight logistics, particularly in last-mile deliveries. The researchers also emphasized that the charging capacity of the EV network at terminals is a key factor in scaling up the adoption of EVs in logistics [22]. Thus, summarizing the views of various researchers, it can be stated that sustainable urban freight logistics requires a comprehensive approach encompassing technological, infrastructural, regulatory, and social aspects. The deployment of electric vehicles, the development of micro-hubs, route optimization, and user engagement must be coordinated to achieve an efficient and sustainable system. In the Lithuanian context, this means that strategically planned solutions and expert assessment can help create a reliable,

efficient, and user-friendly environment for the implementation of electric transport that meets contemporary sustainability goals [8].

2.2. Research Methodology

This study aims to assess the impact of the adoption of electric vehicles in urban freight logistics on sustainability and CO₂ emissions, and to identify the key factors driving their expansion in the context of Lithuanian cities, using expert assessments and scenario simulations to quantitatively evaluate the transformation of the logistics system. The methodological framework of the study consists of three interrelated stages: expert identification of factors, analysis of causal relationships, and dynamic system modelling.

Ten logistics experts participated in the study, all of whom held university degrees and had at least five years of professional experience in international freight transport and urban logistics. The average work experience of the selected experts was approximately 10 years, so their expertise ensured the validity of the study's results.

The survey was conducted in October–December 2025 in three stages. Participants included specialists from the Lithuanian logistics sector, as well as managers of companies or their divisions. The online platform apklausa.lt was used for data collection. The collected data is presented in a clear, structured format, and its analysis can be performed using software such as MS Excel, SPSS (IBM SPSS Statistics 29), or OO Calc (OpenOffice Calc 4.1.15 version).

The questions posed to the experts during the study covered key topics in urban logistics: traffic flows, policy measures and incentives, traffic capacity, the impact of infrastructure, technological aspects of EVs, acquisition costs, as well as environmental and technological aspects and their impact. The Delphi method was applied in the first stage of the study, allowing for the structured identification of the key factors determining the implementation of electric transport in urban freight logistics. Experts from the transport, logistics, and energy sectors participating in the study evaluated and refined the list of factors through several iterative stages until a consensus was reached on the most important criteria. This method reduces the subjectivity of individual assessments and ensures a collective expert opinion. In the second stage, the experts' assessments were converted into fuzzy numbers, which allow for the modelling of linguistic uncertainty, and the DEMATEL method was used to determine causal relationships among the identified factors. From the resulting influence matrix, the impact and dependency indices of the factors were calculated, which allowed for the identification of the main “drivers” of the system—infrastructure and policy measures—and the assessment of their mutual interaction. In the third stage, the results of the DEMATEL analysis were integrated into a system dynamics model, which allows for the simulation of various scenarios for the deployment of electric transport within the urban freight logistics system. The model analyses the interaction of key variables, including the growth of the electric vehicle fleet, the expansion of charging infrastructure, investment dynamics, and changes in CO₂ emissions, enabling an assessment of the long-term impact of policy measures, technological progress, and infrastructure development. The integrated Delphi–Fuzzy–DEMATEL–system dynamics approach enables the combination of expert assessment with quantitative systems analysis, making it possible not only to identify the most important factors in the adoption of electric vehicles but also to forecast their long-term impact on the urban logistics system. Unlike in many previous studies, which rely solely on multi-criteria evaluation methods, this integrated methodological approach allows us to assess not only the importance of the factors but also their causal relationships, thereby forming a comprehensive picture of the potential for electric vehicle adoption and the long-term impact of the scenarios.

The research methodology diagram is presented in Figure 1.

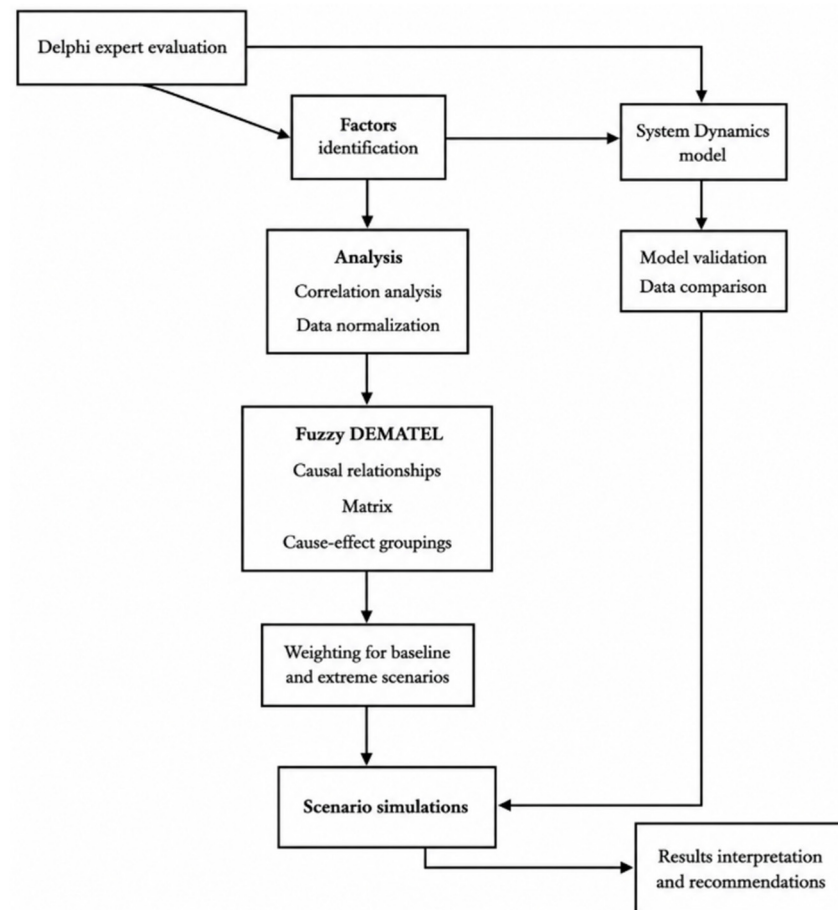


Figure 1. Research methodology model.

To provide a comprehensive overview of the research framework, the methodology of this study is structured into three distinct, sequential phases that bridge qualitative expert insights with quantitative simulation: Phase 1: Identification and Fuzzy-DEMATEL Analysis. A comprehensive literature review and pilot expert interviews were conducted to select the critical constructs affecting electric transport deployment in urban freight logistics. Then, 10 industry and academic experts evaluated the interdependencies using linguistic variables. These evaluations were converted into triangular fuzzy numbers and defuzzified using the Best Nonfuzzy Performance method to build the final matrix of causal relationships. Phase 2: System Dynamics (SD) Model Formulation. The causal insights from Phase 1 directly informed the structural boundaries of the SD model. Variables identified as primary systemic drivers (net-causers) were established as the main policy levers, while variables identified as dependent outcomes (net-receivers) were modeled as endogenous stock-and-flow variables. The equations were calibrated using empirical logistics data and validated via extreme-condition tests. Phase 3: Scenario Simulation and Policy Evaluation. Four distinct policy scenarios (ranging from S1—Baseline to aggressive intervention) were run over a long-term horizon. The simulation outputs were analysed to detect systemic tipping points and formulate strategic recommendations for urban logistics decarbonization.

The study involved a survey of twenty logistics experts, each of whom held a college degree and had at least five years of experience in international freight transport, consolidation, and urban logistics. All experts held a university degree, and their average work experience in the logistics sector was nearly 10 years, ensuring a competent and reliable assessment. The expert group consisted of:

- Six senior managers from freight urban forwarding companies;
- Four heads of logistics associations;
- Four academics with many years of logistics experience;
- Six specialists in electric vehicle technology.

3. Results

The survey identified the following key factors:

A1—infrastructure, number of charging stations, their accessibility, and geographical distribution;

A2—EV acquisition costs, initial price of a city truck, and TCO over the entire service life;

A3—technological progress, battery efficiency, driving range, and quality of maintenance;

A4—policy measures, national and municipal incentives, tax breaks, and EU regulatory measures.

Experts rated the importance of each factor on a five-point scale, where 1 indicated “not very important” and 5 indicated “very important.”

Since the experts’ ratings are expressed as linguistic variables and converted into triangular fuzzy numbers $a \sim_{ij} = [l_{ij}, m_{ij}, u_{ij}]$, the Fuzzy-DEMATEL method was applied by following these structural steps:

- Defuzzification: the fuzzy numbers were converted into crisp values using the Best Nonfuzzy Performance (BNP) method according to the formula:

$$BNP_{ij} = \frac{(u_{ij} - l_{ij}) + (m_{ij} - l_{ij})}{3} + l_{ij} \quad (1)$$

- Construction of the direct influence matrix A: the BNP values are entered into the initial matrix (A), which is then normalized, and the total influence matrix T is calculated.
- Analysis of the interactions between constructs: based on the values obtained from matrix T, two key indicators are calculated: $(D_i + R_i)$ —prominence: indicates the overall importance of a factor and the intensity of its interaction with the entire system. $(D_i - R_i)$ —causality (relation): if the value is positive ($D_i - R_i > 0$), the construct belongs to the group of causes (net-causer) and influences other factors. If the value is negative ($D_i - R_i < 0$), it belongs to the group of consequences (net-receiver) and is influenced by other system variables.

The experts’ ratings form a direct impact matrix:

$$A = [a_{ij}] \quad (2)$$

where

a_{ij} —the effect of factor i on factor j .

The matrix is normalized:

$$X = \frac{A}{\max_j \sum_j a_{ij}} \quad (3)$$

next, the overall influence matrix is calculated:

$$T = X (I - X)^{-1} \quad (4)$$

where

I —unit matrix.

Indicators are calculated for each factor:

$$D_i = \sum_j T_{ij} \quad (5)$$

$$R_i = \sum_j T_{ji} \quad (6)$$

where

D —the sum of the effect of a factor on other factors;

R —the sum of the effects exerted by the factor.

The average values obtained from the experts were normalized by converting them to the 0–1 interval using the following formula:

$$\text{Normalized value} = \frac{\text{average expert rating} - 1}{5 - 1} \quad (7)$$

Triangular fuzzy numbers, denoted by $A^\sim = (l, m, u)$, were used to assess the uncertainty of the expert evaluation for each factor. Here, the parameters l (minimum likelihood estimate), m (maximum likelihood estimate), and u (maximum a priori estimate) were calculated based on the normalized ratings provided by all (n) experts ($n = 20$) using the following formulas:

$$l = \min_{k=1}^n (x_k) \quad (8)$$

$$m = \frac{1}{n} \sum_{k=1}^n x_k \quad (9)$$

$$u = \max_{k=1}^n (x_k) \quad (10)$$

The resulting triangular uncertainty box illustrates the range of expert opinions: the lower (l) and upper (u) bounds represent the extreme expert estimates, while the midpoint (m) represents the consensus average.

Using triangular functions, the indices for all factors were calculated in a similar manner and are presented in Table 1.

Table 1. Expert-based average ratings and fuzzy importance indices for the main factors influencing the development of electric vehicles.

Factor	Expert-Based Average Importance Score	Fuzzy-Number Triangle
Infrastructure	4.6	(0.80; 0.92; 1)
EV acquisition costs	4.10	(0.80; 0.80; 0.95)
Technological advancements	3.90	(0.50; 0.73; 0.80)
Policy measures	3.80	(0.50; 0.70; 0.80)

The expert's average importance scores are presented in Figure 2.

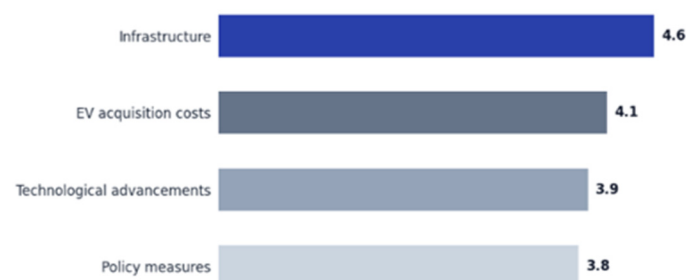


Figure 2. Average ratings of the most influential factors.

Next, all factors are normalized so that their sum equals 1 (100%), according to the formula:

$$w_1 = \frac{\text{median value 1}}{\sum \text{median values for all factors}} \quad (11)$$

$$w_{\text{infr.}} = \frac{4.6}{4.6 + 4.1 + 3.9 + 3.8} = 0.29$$

$$w_{\text{costs}} = 0.25$$

$$w_{\text{techn.}} = 0.23$$

$$w_{\text{poli.}} = 0.23$$

The proportions of factor significance are presented graphically in Figure 3.

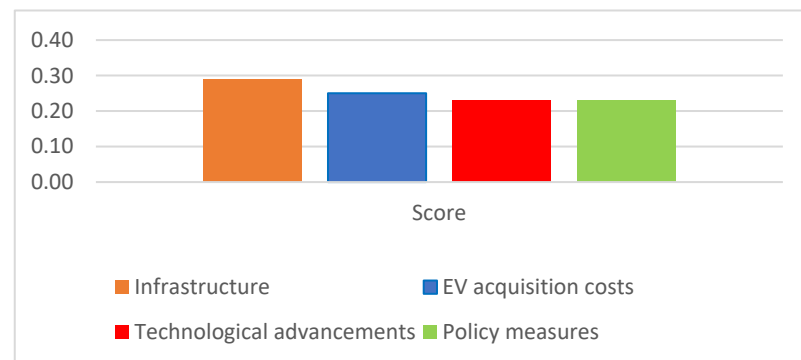


Figure 3. Factor weights based on the median proportion of the total sum of all factors.

These weights are normalized fuzzy median values used to quantitatively assess the importance of factors in the Delphi–Fuzzy model; they indicate the proportional influence of factors on the implementation of EV. This yields relative weights that can be incorporated into a system dynamics model. These weights are integrated into the system dynamics model, enabling the prediction of EV adoption and trends in CO₂ emission reductions. Fuzzy logic enabled the transformation of subjective expert assessments into numerical values that can be used in the model. The fuzzy methodology defines membership functions, which determine the degree to which each factor contributes to EV adoption. After calculating the weights of the factors based on the median proportions of expert assessments, it can be concluded that infrastructure (weight 0.29) and purchase price (0.25) have the greatest influence and importance on the development of electric vehicles in urban freight logistics. Technological progress (0.23) and policy measures (0.23) have a slightly smaller influence. The study also aimed to simulate the impact of factors limiting the expansion of electric vehicles on urban freight transport, thereby identifying critical factors and forecasting the effects of different strategies, taking into account infrastructure, investments, technological advancements and policy measures. Scenario modelling provides important insights into the implementation of electric transport in urban freight logistics [23]. First, it allows for the identification of critical factors that have the greatest influence on system changes—in this case, infrastructure and costs. Second, the model enables a quantitative assessment of the effectiveness of various policy measures and a comparison of their long-term impacts. Furthermore, simulations reveal the synergy among factors, demonstrating that individual interventions are less effective than an integrated combination of measures. Scenario analysis also reduces decision-making uncertainty, as planners can rely on forecasts when making strategic decisions regarding investments and policy.

The model uses the following key variables:

- Number of EVs;

- Infrastructure;
- Level of investment;
- Technological progress;
- CO₂ emissions.

To evaluate alternatives for the deployment of electric transport in urban freight logistics, four different scenarios were developed in the system dynamics model. The scenario analysis allows for an assessment of how different policy measures, infrastructure development and technological changes may affect the integration of electric vehicles into the transport system in the long term. Here are a few reasons why this particular choice was made:

1. **Causal Alignment with Fuzzy–DEMATEL:** The scenarios focus precisely on the key “causal” constructs identified in the first phase of our study (infrastructure and policy measures). By altering variables with the highest (D – R) scores, we ensure that the simulation tests the primary levers of the system rather than arbitrary or secondary factors.
2. **Policy Relevance:** The parameter bounds for the scenarios (pessimistic, baseline, and optimistic) were harmonized with current strategic policy targets (e.g., EU Green Deal and national transport electrification roadmaps), making the outcomes actionable for policymakers.
3. **Boundary and Sensitivity Testing:** The chosen scenarios represent distinct, realistic structural boundaries (e.g., aggressive subsidy injection vs. complete subsidy withdrawal). This approach allows us to stress-test the model’s stability and uncover critical systemic tipping points.

The model simulates four EV deployment scenarios:

S1—Basic Scenario (Current Policy Conditions)—Describes a continuation of the current situation, in which the expansion of electric transport proceeds under existing market conditions and at the current level of government support. In this case, infrastructure development proceeds slowly, investment in electric transport remains limited, and technological progress has a moderate impact on the transformation of the transport sector.

S2—Infrastructure Development Scenario—Envisages faster development of charging infrastructure in cities and logistics hubs. This scenario assumes that investments by the state and municipalities significantly increase the availability of charging stations, thereby reducing one of the main barriers to the adoption of electric vehicles—the lack of infrastructure.

S3—Financial Incentives Scenario—Models a situation where the state more actively supports the purchase of electric vehicles by offering subsidies, tax breaks, or other financial incentives to logistics companies. This scenario allows for an assessment of the impact of economic measures on the pace of electric vehicle adoption and the transformation of the transport fleet.

S4—Integrated Scenario (Infrastructure + Incentives + Technologies)—Combines infrastructure development, financial incentives, and accelerated technological progress. This scenario assumes that the public and private sectors will coordinate their investments in electric vehicle technologies, charging infrastructure, and innovative logistics solutions. This strategy is considered a comprehensive approach to the sustainable transformation of urban logistics.

Scenario analysis allows for an assessment of the impact of various policy measures on the growth of the EV fleet and emissions reduction. To evaluate alternatives for the deployment of electric transport in the urban freight logistics system, several different scenarios were developed in a system dynamics model, allowing for the analysis of potential trajectories for EV deployment under different political and economic conditions. Scenario

analysis is an important tool in transport planning, as it allows for the modelling of potential system changes and the assessment of the long-term impact of different policy measures. The model results allow for a comparison of the effectiveness of different strategies and identify which measures have the greatest impact on the development of sustainable urban logistics. For all scenarios, factor values were determined based on expert assessments from the fields of urban logistics, electric vehicle technology, and transport policy. Each factor was assigned a normalized value between 0 and 1, reflecting its level in a specific scenario: 0—very weak, 1—maximum. The assessments were consolidated using the Fuzzy–DEMATEL method so that the influence of each factor on the growth coefficient r would be proportional to the experts’ assessment. The results are listed in Table 2.

Table 2. Results reflecting the general trends of the obtained averages.

Scenarios	Factors			
	Infrastructure	Acquisition Costs	Technological Progress	Policy Measures
S1	0.60	0.45	0.40	0.35
S2	0.70	0.55	0.40	0.45
S3	0.50	0.75	0.45	0.60
S4	0.70	0.85	0.50	0.75

The result is shown in Figure 4.

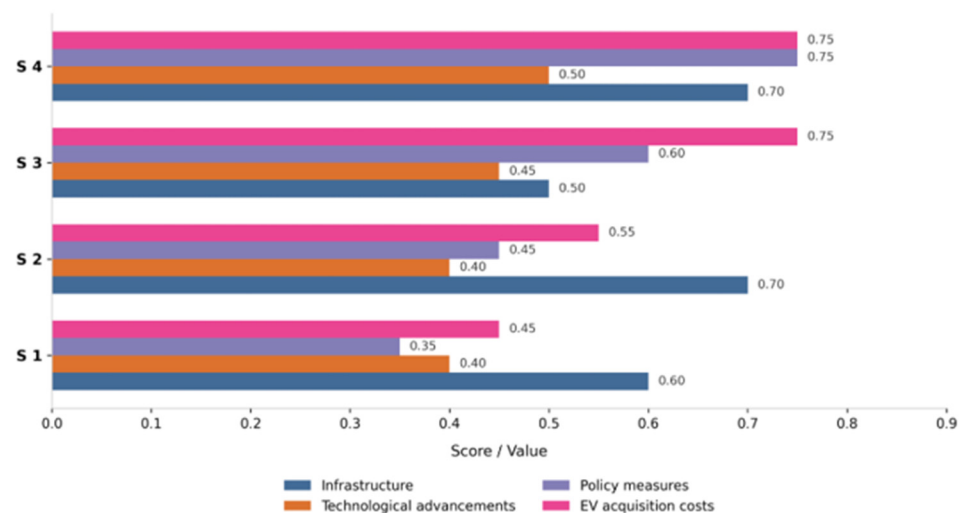


Figure 4. Importance indicators.

A 10-year period (2026–2036) was selected for the modelling.

According to data from the Ministry of Transport and Communications of the Republic of Lithuania, as of 1 February 2026, electric vehicles (categories M1 and N1) accounted for only a small portion of the total vehicle fleet in the Lithuanian Road Transport Vehicle Register [24]. Although there is no precise data on N1 electric vehicles in Vilnius, it can be assumed that they account for about 1% of the total N1 fleet; therefore, this percentage was used in the modelling as an approximate share of N1 EVs in Vilnius [25]. Based on official monitoring data from the European Environment Agency (EEA) [26], average CO₂ emissions from newly registered light commercial vehicles (vans) in the European Union and associated countries are approximately 0.20 kg CO₂/km (WLTP, ~200 g CO₂/km), according to the latest EEA reporting data. This value is used as a representative indicator of

emissions from conventional urban commercial vehicles. Meanwhile, electric vehicles (EVs) are considered to have 0 g CO₂/km at the tailpipe (tank-to-wheel emissions). According to the OECD/ITF report [27] on urban delivery transport, which analyses freight delivery operations in European cities, average annual mileage values often reach approximately 20,000–30,000 km in urban logistics practice due to frequent stops and short delivery routes. This study assumes an average annual mileage of 30,000 km per urban freight vehicle, reflecting typical urban distribution patterns. This assumption is consistent with urban freight modelling approaches that represent city logistics as high-frequency, short-distance delivery systems characterised by intensive vehicle activity and repeated daily routing operations rather than long-haul transport. In this context, activity-based emission models such as the Eco Logistics framework demonstrate that urban freight transport is driven by dense stop-and-go delivery patterns, which inherently lead to substantial annual vehicle activity levels in city logistics systems [28].

This stage of the analysis evaluates CO₂ emissions and their temporal changes, applying fuzzy weights in the calculations to reflect the impact of EV deployment and emission reduction scenarios. Applying the EEA emission factor (0.20 kg CO₂/km) and the assumed annual mileage (30,000 km), the annual emissions of a single conventional vehicle amount to approximately 6 t CO₂. For the simulated fleet of 10,000 vehicles, this corresponds to baseline emissions of approximately 60,000 t CO₂ per year. This baseline serves as the reference level for interpreting the emission reductions achieved under the different EV adoption scenarios. While the baseline emissions are calculated from the assumed fleet characteristics, the simulation model itself estimates emission reductions dynamically according to the changing share of electric vehicles (EVs) in the total fleet.

$$E_T = 60,000 \text{ t}$$

The total fleet of 10,000 vehicles selected for the simulation is based on current and projected data for Class N1 vehicles in Vilnius, as well as national trends. A single conventional N1-class vehicle emits an average of approximately 0.20 kg CO₂/km, although there are no official data on the number of electric vehicles in the urban freight sector in Vilnius, national statistical indicators are therefore used as a contextual basis to justify the selected fleet size and EV proportions (~1.18%) across the entire N1 transport sector. This method provides a clear, quantitative basis for modelling electrification scenarios in the urban logistics system. For the modelling, we will use 1% of the total N1 fleet as the approximate share of electric vehicles in Vilnius. The study employs national N1 vehicle statistics as a proxy indicator for the urban freight vehicle fleet operating in Vilnius. It should be acknowledged that the N1 category encompasses a broad range of light commercial vehicles, not all of which are exclusively used for urban freight logistics. As a result, its application introduces a certain level of approximation when representing the actual urban freight vehicle fleet in Vilnius. This assumption was necessary due to the lack of publicly available official datasets that disaggregate urban freight logistics vehicles from the broader N1 category. Consequently, both the assumed total fleet size (10,000 vehicles) and the baseline electrification level (1% EV penetration) should be understood as modelling approximations rather than precise empirical estimates of the urban logistics sector. Accordingly, the results should be interpreted as indicative, scenario-based estimates designed to analyse system behaviour and relative policy and infrastructure impacts, rather than as exact forecasts of future fleet composition.

$$E_0 = 10,000 \text{ units;}$$

$$EV_0 = 1\% - 100 \text{ EV.}$$

The main result of the model is the growth coefficient for electric vehicles, which is calculated as a weighted combination of four factors. These weights were determined using the Fuzzy–DEMATEL method, and therefore reflect not only the importance of the factors but also their mutual influence within the system. This provides the model with additional analytical validity. The growth coefficient is calculated as follows:

$$r = w_{infr.}INFR + w_{costs}COST + w_{techn.}TECH + w_{poli.}POL \quad (12)$$

where

INFR—infrastructure index (factor values determined based on expert assessments)

COST—economic index

TECH—technology progress index

POL—political measures index

w —factor weights calculated using the Fuzzy–DEMATEL method.

Initial model conditions:

Four scenarios are modelled based on this function.

1. Basic scenario (S1)

$$r = 0.29(0.60) + 0.25(0.45) + 0.23(0.40) + 0.23(0.35)$$

$$r = 0.46$$

2. Infrastructure development scenario (S2)

$$r = 0.29(0.70) + 0.25(0.55) + 0.23(0.40) + 0.23(0.45)$$

$$r = 0.54$$

3. Financial incentive scenario (S3)

$$r = 0.29(0.50) + 0.25(0.75) + 0.23(0.45) + 0.23(0.60)$$

$$r = 0.57$$

4. Integrated approach (infrastructure + incentives + technologies) (S4)

$$r = 0.29(0.70) + 0.25(0.85) + 0.23(0.50) + 0.23(0.75)$$

$$r = 0.70$$

The growth of the EV fleet is modelled according to the principle of a logistic growth function:

$$EV_t = \frac{K}{1 + \left(\frac{K-EV_0}{EV_0}\right)e^{-rt}} \quad (13)$$

where

EV_0 —initial EV quantity;

r —rate;

t —10 years;

K —maximum market potential (market capacity; in this case, 2000 units).

When modelling the expansion of electric vehicles in a system of 10,000 units, the critical parameter is the maximum market saturation level, denoted by the coefficient K . In this study, a sample size of 2000 units is selected. This choice is justified by several key factors:

- **Segmented Market Penetration (SAM):** Although the total system capacity is 10,000 units, based on theories of consumer behaviour (Diffusion of Innovation), the entire population does not consist of early adopters of technology. This corresponds to a realistic portion of the “addressable market,” consisting of consumers who have the necessary infrastructure (private charging stations) and financial means.
- **Infrastructure and technical constraints:** The logistic growth model predicts that growth slows as the system approaches its “ceiling.” In this case, the 2000 units threshold reflects not a lack of demand, but physical system constraints: grid capacity, the density of the public charging station network, and the pace of secondary market development.
- **Saturation point forecast:** The selected value allows for modelling a conservative yet sustainable growth scenario. This helps avoid overly optimistic forecasts, which often fail to account for the skepticism of “laggards” and their long-term attachment to internal combustion engine technologies.

Economic models often include a threshold at which growth stops due to external factors (e.g., limited charging stations or grid capacity). Since the model covers a 10-year period, it may reflect what can realistically be achieved during this time, rather than the ultimate capacity of the entire system. Thus, the coefficient K in this model serves not as a theoretical limit, but as a strategic stabilizer, allowing for a more accurate forecast of medium-term (10-year) changes in the presence of real market barriers. Medium-term electrification of urban commercial vehicle fleets remains constrained by structural, operational, and infrastructural barriers, which results in a partial rather than full transition within typical 10-year planning horizons. Recent empirical studies on electric urban freight systems consistently indicate that optimal or realistic adoption levels for battery-electric delivery vehicles tend to stabilize at a minority share of fleet operations rather than full electrification. For example, simulation-based fleet-mix optimization studies demonstrate that electric vehicles are typically integrated into mixed fleets rather than fully replacing internal combustion engine vehicles, with optimal electrification ratios depending strongly on route structure, demand intensity, and charging availability [29]. In urban freight systems, the transition towards electric vehicles remains constrained by multiple operational and infrastructural factors. Recent studies indicate that vehicle range, charging delays, and insufficient charging infrastructure continue to limit the large-scale deployment of battery electric freight vehicles, particularly in demanding logistics operations [30]. Furthermore, effective electrification depends not only on fleet composition but also on the coordinated planning of charging infrastructure and electricity supply. Evidence suggests that mismatches between charging demand, infrastructure capacity, and spatial deployment significantly reduce the operational feasibility of electric freight fleets, highlighting the importance of integrated transport and energy planning. Quantitative assessments of urban delivery fleet electrification further indicate that feasible EV integration levels in medium-term scenarios typically fall within a bounded range rather than approaching full substitution. Model-based evaluations of medium-duty electric vehicles in urban delivery networks demonstrate that optimal fleet compositions commonly include a mixed ratio of electric and conventional vehicles, with EV shares depending on cost parameters, battery range, and service constraints, rather than reaching complete electrification. Collectively, these findings are consistent with observed transition patterns in European urban freight

systems, where infrastructure limitations, acquisition costs, and operational constraints continue to slow down large-scale electrification of commercial fleets [31]. Accordingly, the assumption of a medium-term electrification ceiling representing approximately 20–30% of the urban commercial fleet can be considered empirically grounded and conservative within a 10-year modelling horizon. Within this framework, the parameter $K = 2000$ vehicles (corresponding to 20% of the total 10,000-unit N1 vehicle fleet) is defined as the most critical control parameter in the logistical optimisation function. This parameter does not represent the theoretical maximum electrification potential of the system, but rather a medium-term realistic adoption ceiling under current infrastructural, economic, and behavioural constraints. Its role in the model is essential, as it directly determines fleet composition limits, charging demand intensity, and routing feasibility under electrified urban logistics scenarios.

1. Basic scenario (S1)

$$EV_t = \frac{2000 - 100}{100} = \frac{1900}{100} \approx 19$$

$$e^{-rt} = e^{-0.46 \cdot 10} = 0.01005$$

$$19 \times 0.01005 + 1 \approx 1.19095$$

$$2000/1.19095 \approx 1680 \text{ EV.}$$

2. Infrastructure development scenario (S2)

$$e^{-rt} = e^{-0.54 \cdot 10} = 0.00452$$

$$19 \times 0.00452 + 1 \approx 1.08588$$

$$2000/1.08588 \approx 1842 \text{ EV.}$$

3. Financial incentive scenario (S3)

$$e^{-rt} = e^{-0.57 \cdot 10} = 0.00335$$

$$19 \times 0.00335 + 1 \approx 1.06365$$

$$2000/1.06365 \approx 1879 \text{ EV.}$$

4. Integrated approach (infrastructure + incentives + technologies) (S4)

$$e^{-rt} = e^{-0.70 \cdot 10} = 0.000912$$

$$19 \times 0.000912 + 1 \approx 1.017328$$

$$2000/1.017328 \approx 1965 \text{ EV.}$$

The results are presented graphically in Figure 5.

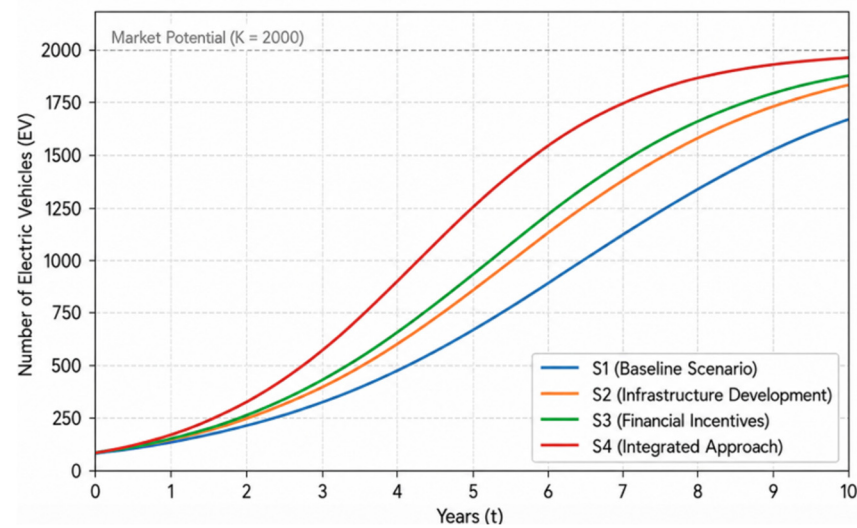


Figure 5. Change in EV over a 10-year period.

The figure shows the evolution of the EV fleet under the four baseline scenarios over the 10-year simulation period. In all scenarios, EV adoption follows a logistic growth pattern, gradually approaching the assumed market saturation level. However, the growth trajectories differ according to the intensity of infrastructure development, financial incentives, technological progress, and policy support. The integrated scenario (S4), which combines infrastructure expansion, financial incentives, and technological progress, results in the highest number of electric vehicles after 10 years. The financial incentive scenario (S3) and the infrastructure development scenario (S2) also accelerate EV adoption compared with the baseline scenario (S1), but to a lesser extent. These results indicate that coordinated improvements across multiple factors are more effective than isolated interventions in promoting long-term EV adoption.

Since the main purpose of promoting electric vehicle (EV) adoption is to lower greenhouse gas emissions, the environmental impact of each scenario was assessed by estimating the potential annual reduction in CO₂ emissions. To maintain a consistent evaluation approach across all scenarios, the calculations were based on the emissions produced by the existing conventional vehicle fleet and the number of electric vehicles projected in each simulation. The baseline annual CO₂ emissions presented in this study were estimated using the average emission rate and annual driving distance of a representative N1-class vehicle. Assuming an emission factor of 0.20 kg CO₂ per kilometre and an average annual mileage of 30,000 km, the estimated annual CO₂ emissions generated by a single vehicle are: $E_t = 6 \text{ t CO}_2$. Since the model considers a fleet of 10,000 vehicles, the baseline annual emissions are:

$$E_T = 10,000 \times 6 = 60,000 \text{ t CO}_2/\text{year}.$$

It is assumed that each electric vehicle replaces one comparable internal combustion engine vehicle with annual emissions of 6 tons of CO₂. The remaining annual emissions are then calculated using the following formula:

$$E = E_T \left(1 - \frac{EV_t}{E_0}\right) \quad (14)$$

where

E_T —baseline annual CO₂ emissions (60,000 t CO₂ per year);

EV_t —the number of electric vehicles in the scenario under consideration;

E_0 —the total size of the transportation system in Vilnius.

The absolute annual reduction in CO₂ emissions is calculated as follows:

$$\Delta E = E_T - E \quad (15)$$

and the relative reduction in emissions:

$$R = \frac{E_T - E}{E_T} \times 100\% \quad (16)$$

1. Basic scenario (S1)

$$E = 60,000 \left(1 - \frac{1680}{10,000}\right) = 49,920 \text{ t CO}_2/\text{year}$$

$$\Delta E = 60,000 - 49,920 = 10,080 \text{ t CO}_2/\text{year}$$

$$R = \frac{10,080}{60,000} \approx 17\%$$

2. Infrastructure development scenario (S2)

$$E = 60,000 \left(1 - \frac{1842}{10,000}\right) = 48,948 \text{ t CO}_2/\text{year}$$

$$\Delta E = 60,000 - 48,948 = 11,052 \text{ t CO}_2/\text{year}$$

$$R = \frac{11,052}{60,000} \approx 18\%$$

3. Financial incentive scenario (S3)

$$E = 60,000 \left(1 - \frac{1879}{10,000}\right) = 48,726 \text{ t CO}_2/\text{year}$$

$$\Delta E = 60,000 - 48,726 = 11,274 \text{ t CO}_2/\text{year}$$

$$R = \frac{11,274}{60,000} \approx 19\%$$

4. Integrated approach (infrastructure + incentives + technologies) (S4)

$$E = 60,000 \left(1 - \frac{1965}{10,000}\right) = 48,210 \text{ t CO}_2/\text{year}$$

$$\Delta E = 60,000 - 48,210 = 11,790 \text{ t CO}_2/\text{year}$$

$$R = \frac{11,790}{60,000} \approx 20\%.$$

The results are presented in Figure 6.

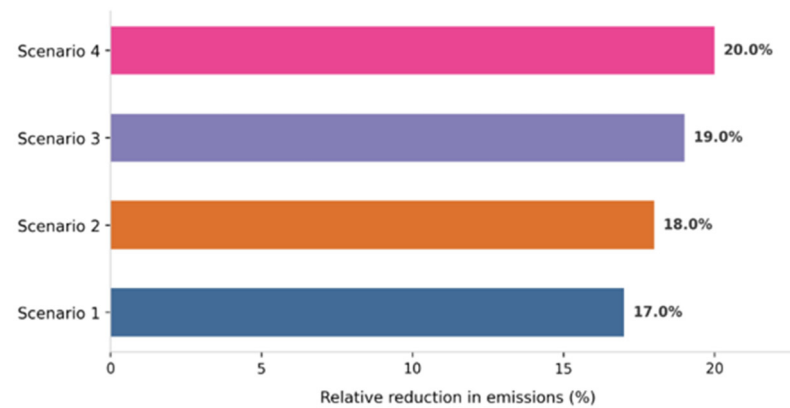


Figure 6. Trends in emissions reduction.

The results of CO₂ emission reductions are directly linked to trends in the number of electric vehicles. In scenarios where the number of electric vehicles is higher, a more significant reduction in emissions is observed. However, the analysis shows that maximum technological or policy implementation does not necessarily result in the greatest environmental impact over the period under consideration. This confirms that an effective emissions reduction strategy must be based on the balanced development of all factors, rather than the maximization of a single factor. The results must be interpreted in light of the model's structure and the assumptions made; the results are not absolute truths but depend on the model.

Based on the developed system dynamics model, four different electric vehicle (EV) deployment scenarios were analysed, reflecting possible political and economic conditions. The model's objective is to assess how various factors may influence the growth in the number of EVs and the reduction in CO₂ emissions over a 10-year period. The results show that the highest number of electric vehicles in 10 years is achieved under the S1 baseline scenario (1680 EVs), with a very similar result observed in the S4 scenario (1965 EVs), while the S3 (1879 EVs) and S2 (1842 EVs) scenarios show slower growth. Although the differences between the scenarios are not particularly large, they reveal trends in how different conditions affect market growth. When assessing the reduction in CO₂ emissions, the results are also similar: the greatest reduction—20%—is achieved in the S4 and S3 scenarios 19%, scenario S2—18% and the smallest reduction—17%—is observed in the S1 scenario. This indicates that greater EV deployment is directly linked to greater emission reductions, although this effect is still relatively small in the short term. In summary, it can be stated that the most effective scenario according to the analysed criteria is S4, which ensures one of the highest numbers of electric vehicles and the maximum reduction in CO₂ emissions. Scenario S3 also yields high results, but the differences between these two scenarios are not significant. Meanwhile, Scenario S1 is the least effective in terms of both EV deployment and emission reduction.

In order to assess the reliability of the developed system dynamics model structure and the system's resilience to external changes, an analysis of extreme scenarios is additionally applied at this stage of the study. Unlike the baseline scenarios (S1–S4) discussed above, this analysis focuses on modelling extreme but realistically possible conditions, allowing for an assessment of the system's behaviour under significant external shocks. This method is widely used in the analysis of complex systems to identify critical vulnerabilities and assess the system's stability under various conditions. In this study, extreme scenarios are generated by modifying the values of key factors—infrastructure (INFR), electric vehicle acquisition costs (COST), technological progress (TECH), and policy measures (POL)—while maintaining the same model structure and growth function. The growth coefficient will

continue to be calculated according to the previously defined formula; therefore, this analysis allows for a direct comparison of results with the baseline scenarios without altering the model's mathematical foundation.

Additionally, four extreme scenarios were formulated:

S5—Economic crisis scenario.

This scenario assumes that, due to an economic downturn, investment in electric transport and charging infrastructure decreases significantly, and companies' financial constraints limit the adoption of new technologies. Accordingly, the values of the COST and POL factors are reduced, and infrastructure development proceeds slowly. This scenario allows us to assess the extent to which the expansion of electric vehicles depends on the stability of economic conditions. In the economic crisis scenario, the values of the COST and POL factors are reduced, based on the assumption that during an economic downturn, both the investment capacity of private companies and the financial capacity of the public sector decrease. Although the nominal costs of electric vehicles may remain unchanged or even decrease in the long term, their affordability decreases in the short term due to limited access to capital, increased financial risk, and more stringent investment decisions. Meanwhile, the effectiveness of policy measures during a crisis may also decrease due to budget constraints, re-prioritization, and reduced funding from subsidies or incentives. Therefore, the model interprets the values of the COST and POL factors not as absolute values, but as indices of their effectiveness and accessibility, which decrease under conditions of economic uncertainty. This assumption is consistent with previous research showing that economic shocks negatively affect investments in innovation and sustainable technologies, especially in the transport sector.

S6—Technological breakthrough scenario.

This scenario assumes that battery technology advances rapidly, the operating costs of electric vehicles decrease, and their efficiency increases. The TECH factor is increased to its highest level, and the cost barrier is reduced. The purpose of this scenario is to assess whether technological progress alone can significantly accelerate the development of electric vehicles.

S7—Intensive policy intervention scenario.

A situation is simulated where the state actively promotes the deployment of electric vehicles by applying subsidies, tax breaks and regulatory restrictions on traditional transport. POL and partial COST factors are significantly increased, and infrastructure development is also accelerated. This scenario allows us to assess the effectiveness of policy measures in transforming the transport system.

S8—Infrastructure stagnation scenario.

This scenario assumes that the development of charging infrastructure is stalled due to financial, technical or planning constraints [31]. The value of INFR remains low, despite the stability of other factors. This scenario allows us to identify the role of infrastructure as a potential "bottleneck" in the development of electric vehicles.

For each scenario, analogously to previous simulations, the growth rate of electric vehicles was calculated and their number was projected after a 10-year period. Table 3 presents the values of the factors (INFR, COST, TECH, and POL) used for scenarios S5–S8.

The same calculated weights are used for the calculation:

$$w_{infr.} = 0.29$$

$$w_{costs} = 0.25$$

$$w_{tech.} = 0.23$$

$$w_{poli.} = 0.23.$$

Table 3. Values of factors.

Scenario	Factors			
	INFR	COST	TECH	POL
S5	0.40	0.30	0.40	0.30
S6	0.60	0.70	0.95	0.50
S7	0.80	0.80	0.60	0.95
S8	0.30	0.60	0.60	0.50

The growth rate is calculated using the same formula:

$$r = w_{infr.}INFR + w_{costs}COST + w_{techn.}TECH + w_{poli.}POL$$

The growth of the EV fleet is modelled according to the same principle of the logistic growth function:

$$EV_t = \frac{K}{1 + \left(\frac{K - EV_0}{EV_0} \right) e^{-rt}}$$

1. Economic crisis scenario (S5)

$$r = 0.29(0.40) + 0.25(0.30) + 0.23(0.40) + 0.23(0.30)$$

$$r = 0.35$$

$$EV_t = 1270 \text{ EV.}$$

2. Technological breakthrough scenario (S6)

$$r = 0.29(0.60) + 0.25(0.70) + 0.23(0.95) + 0.23(0.50)$$

$$r = 0.68$$

$$EV_t = 1959 \text{ EV.}$$

3. Political intervention scenario (S7)

$$r = 0.29(0.80) + 0.25(0.80) + 0.23(0.60) + 0.23(0.95)$$

$$r = 0.79$$

$$EV_t = 1986 \text{ EV.}$$

4. Infrastructure stagnation scenario (S8)

$$r = 0.29(0.30) + 0.25(0.60) + 0.23(0.60) + 0.23(0.50)$$

$$r = 0.49$$

$$EV_t = 1752 \text{ EV}$$

The results are presented graphically in Figure 7.

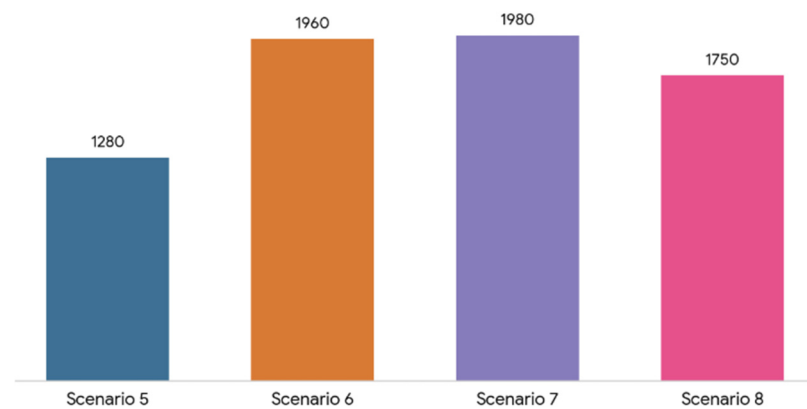


Figure 7. EV number dynamics over a 10-year period under extreme scenarios.

As expected, the economic crisis scenario (S5) results in the lowest level of EV adoption, reaching only 1280 electric vehicles by the end of the 10-year simulation period. Reduced investment capacity, constrained infrastructure development, and weaker policy support collectively slow the diffusion of electric vehicles, leading to the weakest market growth among all scenarios. In contrast, the technological breakthrough scenario (S6) significantly accelerates EV adoption, with the total number of electric vehicles increasing to 1960. Rapid technological advancements, improved battery performance, and declining operating costs enhance the attractiveness of EVs and substantially increase their market penetration. The intensive policy intervention scenario (S7) achieves the highest level of EV adoption, reaching 1980 electric vehicles. Comprehensive financial incentives, supportive regulatory measures, and accelerated charging infrastructure development create the most favourable conditions for long-term EV deployment, resulting in the strongest market expansion. Although the infrastructure stagnation scenario (S8) still generates moderate growth, reaching 1750 electric vehicles, the limited expansion of charging infrastructure constrains the full potential of technological improvements and policy support. This finding highlights the essential role of infrastructure availability as a prerequisite for widespread electric vehicle adoption. Overall, the extreme scenario analysis demonstrates that technological innovation and strong policy interventions are the primary drivers of EV adoption, while unfavourable economic conditions substantially impede market development. The findings are consistent with the assumptions of the logistic growth model and emphasize the importance of coordinated technological, economic, and policy measures in facilitating the transition to electric mobility. A comparison of EV growth trends across all scenarios is presented in Figure 8.

Comparison of scenarios allows for a clear identification of the system's sensitivity to different combinations of factors. It has been observed that the highest number of electric vehicles is achieved not under maximum factor values, but under balanced conditions.

Extreme scenarios further highlight this trend, particularly in the cases of political intervention (S7) and technological breakthrough (S6). The results show that the system's behaviour remains sensitive to external changes, but different factors have unequal effects. In the economic crisis scenario (S5), a significant slowdown in the development of electric vehicles is observed, confirming a strong dependence on investment and financial incentives. Meanwhile, the technological breakthrough scenario (S6) shows faster growth; however, its impact is not maximal if infrastructure and policy measures are not suffi-

ciently developed. The intensive policy intervention scenario (S7) demonstrates one of the strongest positive effects, revealing that coordinated public policy measures can significantly accelerate system transformation. At the same time, the infrastructure stagnation scenario (S8) confirms that even under favourable economic and technological conditions, a lack of infrastructure remains a critical limiting factor. In summary, this analysis allows for an extended interpretation of the baseline scenarios and provides additional insights into system resilience. It was found that the development of electric vehicles in urban freight logistics is particularly sensitive to economic and infrastructural changes, while technological progress and policy measures are most effective only under favourable systemic conditions. These results confirm that a sustainable transformation of the transport system requires not only strengthening individual factors, but also ensuring their mutual compatibility and long-term stability. The application of a system dynamics model in this study allows not only comparison of different scenarios, but also understanding of the interactions between policy measures, economic factors, and technology diffusion. Such a model is useful for decision-makers, as it enables the prediction of possible consequences even before specific measures are implemented. Although a 10-year period does not reveal the full potential of electric vehicle development, the model shows general trends and helps identify the most effective development scenarios.

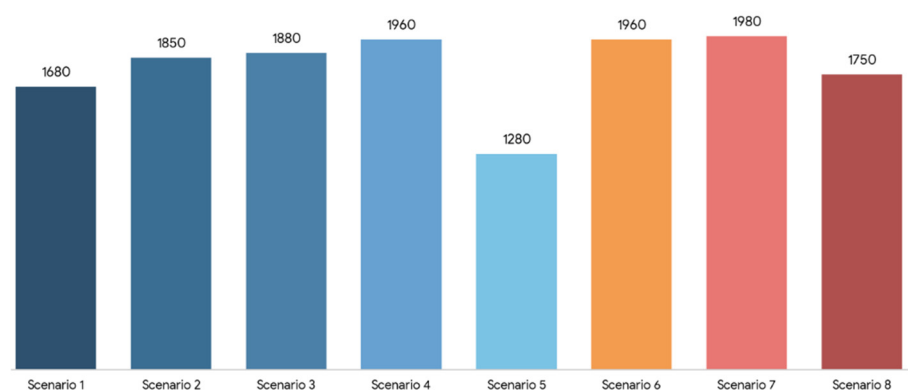


Figure 8. Comparison of EV numbers across all scenarios (S1–S8).

Model Validation

To enhance the credibility and analytical robustness of the developed system dynamics model, a comprehensive multi-stage validation procedure was implemented. Due to the limited availability of detailed historical data concerning the deployment of electric N1 freight vehicles in Vilnius, the validation process primarily concentrated on structural coherence, behavioural realism, expert assessment, and comparison with trends identified in earlier European urban freight transport studies. The first stage involved structural validation, which examined whether the causal relationships embedded within the model accurately reflect the behaviour of urban freight transport systems described in existing scientific literature. The interactions among charging infrastructure expansion, vehicle acquisition costs, technological advancement, policy incentives, and EV adoption were established based on prior empirical and theoretical research in sustainable urban logistics and transport electrification. The model follows a diffusion-oriented system dynamics framework, where infrastructure accessibility, economic feasibility, and governmental support collectively affect technology adoption through feedback loops and nonlinear system interactions. The second stage focused on behavioural validation by evaluating whether the simulated EV adoption pathways exhibit realistic long-term dynamics. The simulation produced characteristic S-shaped logistic growth patterns that are widely recognised in studies of technological diffusion and EV market penetration. This behaviour aligns with

Rogers' Diffusion of Innovation theory, as well as previous research on urban transport electrification, where adoption initially progresses slowly, subsequently accelerates, and eventually stabilises due to economic and infrastructural limitations. Consequently, the generated adoption trajectories are consistent with theoretically anticipated system behaviour. A third validation stage was carried out during the Delphi–Fuzzy DEMATEL analysis. Experts participating in the study assessed not only the significance of the analysed variables but also the logical consistency of relationships among infrastructure development, economic conditions, technological progress, and policy interventions. According to expert feedback, the model structure appropriately represents the operational characteristics of urban freight logistics systems and the primary barriers affecting EV implementation in real-world conditions. This expert-based assessment strengthens the face validity of the proposed model. In addition, the simulation outputs were compared with recent electrification trends identified in similar European urban freight transport studies. Earlier investigations conducted in Germany, France, the United Kingdom, and other European logistics markets demonstrate that the diffusion of electric commercial vehicles continues to be heavily constrained by insufficient charging infrastructure, operational challenges, limited battery range, payload restrictions, and high purchase costs. Therefore, the moderate EV penetration levels generated by the model over the analysed 10-year period are consistent with empirical evidence observed in comparable European logistics environments. This comparison further confirms the plausibility of the selected market saturation assumptions and the overall behavioural patterns of the model. Finally, the model's sensitivity under extreme conditions was evaluated through the analysis of extreme scenarios (S5–S8). These scenarios enabled assessment of system resilience in the presence of economic disruptions, stagnating infrastructure development, rapid technological breakthroughs, and intensive policy interventions. Across all tested scenarios, the model maintained internally consistent behaviour and preserved coherent relationships between system variables and expected policy outcomes. These findings provide additional support for the robustness and reliability of the developed modelling framework. Nevertheless, the validation process remains constrained by the limited availability of detailed local statistical data regarding urban freight EV deployment in Vilnius. As a result, the model should primarily be considered a strategic scenario-analysis and decision-support instrument rather than a precise forecasting tool. Despite these limitations, the applied validation procedures enhance confidence in the model's suitability for examining medium-term urban freight electrification trends and policy alternatives within the Lithuanian context.

4. Discussion

The results of the study showed that the development of electric vehicles (EVs) over a ten-year period significantly depends on the applied political and economic conditions, but in the baseline scenarios (S1–S4) the differences between them remain relatively small. The system dynamics model simulation revealed that the largest number of electric vehicles is achieved in the S7 scenario (1986 EVs), and a very similar result is observed in the S4 scenario (1965 EVs). The S3 scenario (1879 EVs) reflects the average development trajectory, while the S5 scenario (1270 EVs) remains the least effective. These results show that even when applying different political and economic measures, the system response is quite moderate. This allows us to conclude that the development of electric vehicles in the period under consideration is limited by structural factors—the pace of infrastructure development, technology diffusion and consumer behaviour. In other words, the system is characterized by inertia, and more significant changes require a longer period or stronger, comprehensively applied interventions. The results of the reduction in CO₂ emissions confirm this trend. The largest decrease is found in the S4 and S3 scenarios

(20%, 19%), the S2 scenario—18%, and the smallest in the S1 scenario (17%). This shows that the growth in the number of electric vehicles alone is not sufficient to achieve a significant environmental effect. For a greater impact, additional measures are necessary, such as decarbonization of energy production or efficiency of the transport system. The additional analysis of extreme scenarios (S5–S8) essentially complements these insights and allows a better understanding of the sensitivity of the system. Unlike the baseline scenarios, where growth is uniform and limitedly variable, extreme scenarios show a pronounced reaction of the system to the imbalance of individual factors. In the economic crisis scenario (S5), the number of electric vehicles decreases to approximately 1270 units, which is significantly less than in all S1–S4 scenarios. This clearly shows that financial factors are critical and can significantly hinder the transformation of the system. The technological breakthrough scenario (S6) (around 1959 EV) and the political intervention scenario (S7) (around 1986 EV) show that even when one factor is strengthened, the result remains similar to the baseline scenarios. This allows us to conclude that individual measures do not create a significant breakthrough. The infrastructure stagnation scenario (S8), which reaches about 1752 EVs, confirms the importance of infrastructure as a limiting factor. When compared to S1 and S4, it can be seen that even under favourable conditions in other areas, the lack of infrastructure can reduce the final result to the level of less efficient scenarios. The comparative analysis between S1–S4 and S5–S8 allows us to formulate a fundamental conclusion: in the base scenarios, the system develops stably, since the factors are relatively balanced, while the extreme scenarios reveal that the imbalance of the system leads to a disproportionately large negative impact. This confirms that the development of electric vehicles is not the result of a single factor, but the interaction of the entire system. In summary, it can be stated that the system dynamics model reveals two essential properties of the transport system: inertia and sensitivity to imbalance. Over a ten-year period, even the most favourable scenarios do not create exponential growth, and more significant changes are possible only by ensuring the coordinated operation of all factors—economic, technological, political and infrastructural. The final conclusion of this study is that the effective development of electric vehicles in urban freight logistics is possible only by applying a complex, systemic approach. System dynamics modelling in this case proves to be an extremely useful tool, allowing us not only to evaluate the results of different scenarios, but also to understand the very principles of the system's operation and identify the most effective long-term policy directions. The results of this study are in line with recent research that emphasizes the importance of charging infrastructure and policy measures in accelerating the deployment of electric vehicles in urban freight logistics (e.g., 2024–2026 studies). As in recent multi-criteria and systematic analyses, the results confirm that high initial investments and insufficient infrastructure remain the main obstacles to large-scale deployment. However, in contrast to many studies that assess these factors separately, this work shows that their impact is nonlinear and strongly dependent on their interaction. Recent research on sustainable urban logistics increasingly emphasizes the importance of integrated solutions that combine infrastructure planning, technological innovation and policy measures. Based on this perspective, the study results show that improvements in one dimension (e.g., battery technology or cost reduction) are not sufficient to significantly accelerate the deployment of electric vehicles without parallel progress in other important areas. This confirms the growing consensus that system-level coordination is essential for effective transport decarbonization. Furthermore, compared to scenario-based modelling studies, this work stands out by including extreme scenario analysis, allowing for the assessment of system sensitivity under high uncertainty. This aspect is particularly important in the context of rapidly changing energy markets, regulatory environment and technological advancement. The results obtained highlight

the importance of system resilience and adaptive policy-making, which are increasingly identified as essential factors in research on sustainable urban mobility development. The practical implications of this study are particularly relevant for Lithuania, where the transition to electric urban freight transport is still at an early stage and requires coordinated policy and infrastructure development. The results of the study provide a basis for decision-making that can help national and municipal authorities prioritize investments in charging infrastructure, financial incentives and regulatory measures to accelerate the deployment of electric vehicles in the logistics sector. From an EU policy perspective, the study findings support the objectives of the European Green Deal and the Fit for 55 packages, emphasizing the need for integrated, system-level approaches to the decarbonization of transport. The identified nonlinear interactions between infrastructure, costs, technologies and policies indicate that fragmented policy measures may not be sufficient, and highlight the importance of coordinated and multi-level governance to achieve sustainable urban mobility goals in European cities.

5. Conclusions

The scientific literature emphasizes that urban logistics has unique features: it is very sensitive to environmental influences, intensive movement of cargo and parcels occurs, and processes require constant optimization. The goal of this optimization is to improve route planning, the layout of logistics centers, and the efficiency of cargo consolidation and deconsolidation, often using the principles of public–private partnership (PPP). When analysing urban logistics problems, the authors note the challenges of the “last kilometer” related to the operation of distribution networks, and draw attention to the issues of the “first kilometer”, which have been little studied so far. The distribution of cargo flows in the city is mainly determined by the geographical location of the city, the localization of industrial and commercial facilities, and the location of distribution centers in the city center and on the outskirts. Mobility in the city is also affected by road infrastructure, traffic rules, and the availability of parking spaces. The data-processing methodology allowed us to ensure the reliability of the research results. The analysis of extreme scenarios complemented the results of the baseline scenarios and allowed us to assess the system’s resilience to extreme conditions. It was found that the development of electric vehicles is particularly sensitive to economic and infrastructural changes, and the strengthening of individual factors does not always lead to a higher final result due to the nonlinearity of the system and saturation effects. This emphasizes the importance of a complex and balanced approach in shaping transport policy and planning sustainable urban logistics development. The system dynamics model allowed us not only to assess the final results of the scenarios, but also to understand the causal relationships and the behaviour of the system over time, including nonlinearity and feedback loops. Building on these findings, a clearer future research agenda can be outlined. Further studies should aim to extend the model by incorporating more granular behavioural parameters, particularly consumer and operator decision-making mechanisms, which may significantly influence EV adoption dynamics. In addition, integration of real-time operational data from urban freight systems would allow for higher model precision and improved calibration under dynamic conditions. Another important research direction is the inclusion of energy system interactions, such as electricity grid constraints and renewable energy penetration, which may directly affect the feasibility of large-scale EV deployment in urban logistics. Moreover, cross-city comparative studies across different European urban contexts would strengthen the external validity of the model and allow for more robust generalization of results. Finally, future work could explore the integration of artificial intelligence and machine learning techniques with system dynamics modelling to improve predictive accuracy and enable adaptive scenario

optimisation under rapidly changing technological and policy environments. In the long term, it is necessary to strengthen coordinated policy measures, because the changes achieved over a 10-year period, although positive, are not sufficient for a fundamental transformation of the transport system. The study has shown that system dynamics modelling, supplemented by extreme scenario analysis, is an effective tool for assessing not only growth trends, but also the vulnerability and resilience of the system. The results of this study can be practically applied in shaping national and municipal transport policies and planning the sustainable development of urban freight logistics. The developed integrated Delphi–Fuzzy–DEMATEL–system dynamics model can be used as a decision support tool, allowing us to assess the impact of different strategic alternatives on the development of electric vehicles and the reduction in CO₂ emissions. The model can also be adapted to the needs of specific cities or logistics companies, taking into account their infrastructural, economic and regulatory characteristics. Further research could be focused on expanding the model to include additional variables, such as consumer behaviour, energy network load or real-time transport data. It is also appropriate to conduct empirical studies in different cities or regions to validate the model results and increase their generalizability. In the future, it is important to integrate artificial intelligence and big data analytics methods, which would allow for even more accurate forecasting of electric vehicle development scenarios and optimization of urban logistics systems in dynamically changing conditions.

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