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FORECAST METHODS FOR INVESTMENT OF COUNTRY WIDE ELECTRIC VEHICLE CHARGING STATIONS: LITHUANIAN CASE

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Abstract. The aim of this article is to present a complex model for forecasting the required investments based on the forecast of the increase in the number of electric vehicles and their demand for energy and investments. Scientific problem is that current approach on forecasting of electric vehicles is to abstract, forecast models can't be transferred from country to country. This article proposes a model of forecasting investments based on the forecast of the increase in the number of electric vehicles and their demand on energy. The findings of the Lithuanian case analysis, which is expressed in three scenarios, focuses on two trends. The most promising scenario projects 319 470 electric vehicles by 2030 which will demand for 1.09 TWh of electricity, representing 8.4–9.9 percent of the total energy consumption in the country. It demands EUR 230.0 million in the low-voltage grid and EUR 209.0 million in the charging stations. Main limitations are related to statistics available for modelling and human behaviour uncertainty, especially in evaluation impact of measures to foster use of electric vehicles.

Keywords: electric vehicles, charging stations, demand forecast.

JEL Classification: O18, O21, C15.

Introduction

The aim of this article is to present a complex model for forecasting the required investments based on the forecast of the increase in the number of electric vehicles and their demand on energy and investments. In the period of 2008–2013, it was expected that electric vehicles would soon be available in the automotive market in Europe (Glerum et al., 2013) and in the United States (Musti & Kockelman, 2011). Many researchers have argued that new mathematical models are needed to understand and predict the impact of this change on market shares. In the beginning, the behaviourist approach was very important as statistical data on electric vehicles (EVs) was absent. According to Glerum, the Discrete Choice Experiment methodology has been widely applied to analyse the demand for alternative fuel vehicles and electric vehicles (2013). Scientific problem is that current approach on forecasting of electric vehicles is to abstract, forecast models can't be transferred from country to country. This article proposes a model of forecasting investments based on the forecast of the increase in the number of electric vehicles and their demand on energy. The article presents three forecast methods for investment of country-wide electric vehicle charging stations in example of Lithuanian case. Chapter 1 represents the variety of scientific approaches in electric vehicles forecasting. The general assumptions and three different methods for forecasting of scenarios are described in Chapter 2. Chapter 3 presents main results of forecasting of electric vehicle fleet size, energy consumption, need of electric charging infrastructure, and demand for investments. Main limitations are related to statistics available for modelling and human behaviour uncertainty, especially in evaluation impact of measures to foster use of electric vehicles.

1. Review of literature

The growing number of EVs became challenging to the traditional distribution grid with a new set of consumption curves. Accordingly, Gerosier et al. (2019) focused

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their research on different consumption scenarios for a single EV and assessed the expected impact of the additional EVs on the grid by 2030, assuming that the future charging habits will follow the current behaviour. Moreover, Gough et al. (2017) proved that there is a significant impact on the grid capacity in the techno-economic analysis of the EV-based energy storage. Gough et al. (2017) employed a hybrid time-series/probabilistic simulation environment using real-world data, which was applied in the analysis of vehicle-to-grid electricity trading with vehicles, buildings and markets. Gough found that the key parameters are the electric vehicle electricity sale price, the battery degradation costs, and the infrastructure costs (2017). Kim et al. (2017) presented a multicriteria model for forecasting the amount of battery electric vehicles (BEV). Using the exponential smoothing method, Peng et al. (2014) elaborated on the EV demand forecast, focusing on developed countries. They found that the differences are still too vast across the different countries and regions, and, as a result, the forecasting methods cannot be universal and must be adjusted according to the specifics of the region or country. Tamor et al. (2013) presented a purely statistical approach, albeit regression models, as used for prediction, require a sufficient amount of historical data.

Jing et al. (2021) focused on the different types of EVs. Their research shows that different methodological approaches are necessary to predict the patterns of personal, commercial, passenger, and freight vehicles, as such patterns depend on the charging frequency, charging capacity, and convenient charging times. Björnsson and Karlsson (2017) and Karlsson (2017) paid special attention to BEV and plug-in hybrid electric vehicles (PHEV) as both types of EVs have different metrics in terms of the charging frequency, charging capacity and convenient charging time. The authors found that a PHEV, in general, will have a higher total cost of ownership than a BEV, provided that the use of the BEV is optimised (Hagman et al., 2016). The research results by Lin et al. (2013) and Wu et al. (2015) were similar. However, the PHEV will be increasingly favoured if, for example, drivers cannot, or do not want to, optimise their usage. In addition, the PHEV and the BEV are not perfect substitutes for EV.

The increase in the number of electric vehicles is leading to an increase of energy demand at global, regional, and national levels. In their article, Hong et al. reviewed recent research progress on probabilistic energy forecasting (2016). Moon et al. (2018) stated that there is a need to accurately predict the charging demands for EVs in order to effectively meet the demand for additional electricity while ensuring the stability of the power grid.

Moon et al. (2018) identified the changes in the electricity charging demand based on consumer preferences for EVs, their preferred charging time, and the types of electric vehicle supply equipment (EVSE) and covered the relevant issues that must be considered when constructing the EV infrastructure. A very important finding was that people tend to prefer charging at fast public EVSEs during peak load times, showing that consumers consider the trade-offs between the full charge time and the price for charging. Accordingly, Mwasilu et al. (2014) emphasised the need for the integration of renewable energy sources (RES) in the vehicle-to-grid interaction. They found that the presence of RES (wind and photovoltaic solar energy) is soaring in the power system. However, the intermittent nature of RES power output poses different challenges on the planning, operation and control of the power networks. On the other hand, the deployment of EVs in the energy market could compensate for the fluctuations in the electric grid (Haben et al., 2014).

Another important aspect for predicting the EV market growth is climate change policies and the attitudes of car users. The increasing pressure on politicians to shift their political measures toward the acceleration of the EV usage is having a significant impact on consumer choice. Reducing CO2 emissions is becoming vital not only in terms of the economy, but also in the mindset of society (Pasaoglu et al., 2012). In their study, Fu and Fu (2021) chose the double species model to predict the growth trajectory of electric vehicles under mutually competitive conditions between the electric vehicles and the internal combustion engine vehicles in China. Although the total cost of ownership of EVs is still more advantageous compared to the internal combustion engine vehicles (Jochem et al., 2016), the political leverage is still vital in the prediction model. The internalisation of pollution costs in the form of CO2 taxes (Manjunath & Gross, 2017) and the dedicated subsidies (Wikstrom et al., 2016) for EV usage are the two forms of political measures that are in place.

The decarbonisation pattern gathered momentum around the world in 2015–2020. As a rapidly growing market, China responded to the global climate change policy. Chai et al. (2016) presented a comprehensive study of the road transportation energy consumption demand in China. A year later, Zhang et al. (2017) estimated the electric vehicle market penetration and the related impact on the energy consumption and CO2 emissions in Beijing. The contingent valuation method, presented by Dong (2022), was used to conduct a statistical analysis of a questionnaire survey on the willingness of consumers to accept EV subsidies in Nanyang City, Henan Province, China.

In 2020, the European Commission (2019a) proposed a legislation to ensure a safe, circular and sustainable battery value chain for all batteries, including the battery supply in the growing market of electric vehicles. All EU countries were obliged to introduce National Energy and Climate Plans (NECP) with clear indicators on the transport greenhouse gas (GHG) emissions for 2030. With regards to the targets set by countries for 2030 in terms of the EV numbers – both the total and the percentage of new acquisitions of vehicles – it is difficult to predict what effect it will have on the total energy usage in each country. Moreover, as the national regulations and the market for electric vehicles are quickly gaining momentum, there is an urgent need for an intelligent integration of the energy and mobility systems, as proposed by Wolf and Korzynietz (2019). The researchers also stated that a promising innovation path includes the consequent application of smart and flexible charging concepts and the adaptation of the regulations and roles in combination with the consequent use of renewable energy sources.

As per above, there is a wide range of approaches, methods and criteria that the authors of this article used to predict the number of EVs and the needs for electricity, as well as the number and the parameters of the charging stations. The aim of this article is to present a complex model for forecasting the required investments based on the forecast of the increase in the number of electric vehicles and their demand for energy and investments. The model includes a behaviourist approach based on the total cost of ownership model, as well as calculations on the efficient usage of the EV charging points. The model takes into account all types of vehicles, including personal, commercial, freight and passenger vehicles. Chapter 2 presents the general framework of the model and the key assumptions that were used to test the model in Lithuania.

Lithuania is an EU country with a National Energy and Climate Plan, which makes significant implications in demand of electric vehicles, EV charging points and the energy supply needs at the national level in 2022–2030. Chapter 3 presents the forecasting results, including three scenarios and the implications of these scenarios on the investment needs in the electricity distribution grid and the EV charging network.

General conclusion of Literature analysis is that there is still a lack of a single recognised model to predict EV future trends and a lack of investment planned by politicians to support these trends. Important findings from Literature analysis comes to the fact that various policy measures, such as subsidies, tax discounts, zero emission zones are contributing the growth of electric vehicle fleet significantly.

2. Methodology

Several different methods were used to forecast the investment needs generated by the growth of the electric vehicle market.

The general algorithm of forecasting consists of several consecutive phases:

1) Forecasting the number of electric vehicles.
2) Forecasting the energy needed for electric vehicles, based on the forecast (1) and the predicted usage level of these vehicles.
3) Forecasting the charging station number with the expected technical capacities and characteristics of these charging stations based on the forecasts (1) and (2).
4) Forecasting the need to upgrade the low-voltage grid based on the forecast (3).
5) Calculating the total investment needed based on the results of the forecasts (3) and (4).

2.1. Phase 1 methodology

The general approach in scenario modelling tends to have three scenarios with each scenario being based on a different method of forecasting. Typically, in any kind of forecasting, scenarios include a pessimistic, a realistic, and an optimistic scenario, using the same methods for all three scenarios.

In our case, we did not name the scenarios as pessimistic, realistic, or optimistic in the very beginning. The first scenario was created using pure statistics. Statistics for all types of vehicles (M1, N1, M2, N2, M3, N3) were taken from the official register of vehicles "Regitra" (Lithuanian National Vehicle Register). From 2014 to 2020, annual data was collected for each type of vehicle, the number of new vehicles registered in the country each year, and the number of used vehicles registered in the country each year. The same statistical data was collected for electric vehicles. A large-scale correlation analysis was applied to check whether vehicle statistics are correlated with the country's macroeconomic indicators such as export (in currency and tonnes), import (in currency and tonnes), GDP, annual personal income, domestic freight transport volumes, population, and passenger numbers. In addition, we cross-correlated vehicle fleet data, in particular new vehicle registrations and EV registrations. The large-scale correlation analysis resulted in a very strong correlation of countries' GDP and personal income with new vehicle registrations and electric vehicle registrations in the M1 segment. Further, we estimated The World Bank's forecast for Lithuania's GDP by 2030. Based on a regression between GDP and EV, the forecast for EVs was calculated using the regression function in MS Excel. The formulas (1)–(6) are adapted for each Phase based on the general method for forecasting the STAT scenario.

$$EVF_{STAT} = f\left(GDP, VR, IN\right), \tag{1}$$

where EVF_{STAT} – the size of the electric vehicle fleet in the STAT scenario; GDP – gross domestic product; VR – annual vehicle registrations; IN – personal income average.

The other two scenarios to forecast the number of EVs were not statistical. One scenario was built on the assumption that the targets set by the national government will be met by 2025 and 2030. The targets were set out in the Law on Alternative Fuel and the Law on Green Procurement (Table 1). However, the targets do not directly correspond to the EV fleet size, but rather to a formal requirement of what percentage of vehicles are allowed to be registered as EVs and what percentage are allowed to be registered as internal combustion engine vehicles in 2025 and 2030.

Table 1. Target set in the Law of Alternative Fuel (source: Law of Alternative Fuel)

Type of vehicle	Required minimum Percentage of EV in new registration of vehicles annually	
	Y 2025	Y 2030
M1	10%	50%
M1 (taxi)	60%	100%
N1	30%	100%
M2	60%	100%
N2	8%	16%
M3	80%	100%
N3	0%	0%

The forecast is based on the target (GOAL) scenario is built on the assumption that the formal requirement set out in the legislation will be achieved. The percentage of EVs in all vehicles registered in 2030 is calculated backwards for 2026–2029, using an exponential progression formula back to 2025. The backward exponential formula was also used for 2022–2024 from the 2025 target to the 2021 factual data.

Taking into account the projected annual new vehicle registrations for the period 2022–2030 and the November 2021 statistics, the total fleet of EVs in each year from 2022 to 2030 was estimated. It was assumed that any registered EVs will also be in use in 2030 and will not be de-registered. The assumption was crosschecked in a programme of qualitative interviews with EV stakeholders such as car dealers, consumer associations and experts. The interview showed that there are great expectations for EVs in the domestic used EV market, so in any case of EV stay in the national fleet.

$$EVF_{GOAL} = f\left(VRP_{2025}, VRP_{2030}\right), \quad (2)$$

where EVF_{GOAL} – the size of the electric vehicle fleet in the GOAL scenario; VRP_{2025} – annual vehicle registration projection for 2025; VRP_{2025} – annual vehicle registration projection for 2030.

The GOAL scenario does not estimate any measures that are taken under national legislation, but it clearly shows what the country expects to achieve by introducing formal requirements for vehicle registration. However, certain measures are very important to support the growth of the EV fleet and consumer behaviour. Moreover, the government has set out a list of measures at national and municipal levels to support EV development.

The following measures have been assessed:

- government subsidy for the purchase of electric vehicles;
- restrictions on access to 5 major city centres planned by the city councils of Vilnius, Kaunas, Klaipeda, Siauliai and Panevezys;
- an annual CO2 tax for conventional vehicles depending on their emissions, set by the government;
- an emissions-based registration fee for internal combustion engine vehicles, set by the government;
- further increases in taxes on diesel and petrol.

The MEAS scenario also takes into account the total cost of ownership (TCO). It was assumed that an EV would only be chosen if the TCO of owning an EV is positive compared to the TCO of an internal combustion engine vehicle. Some measures have a significant impact on the TCO balance (taxes, fees and subsidies) and their impact was therefore estimated in the TCO model. Measures such as restricting access to the city centre would be more effective if it was assumed that the part of the fleet that requires access to the city centre would be replaced by EVs.

$$EVF_{MEAS} = f\left(MEAS_{GOV}, MEAS_{MUN}, TCO\right), \quad (3)$$

where EVF_{MEAS} – the size of the electric vehicle fleet in the MEAS scenario; $MEAS_{GOV}$ – government measures; $MEAS_{MUN}$ – municipal (city) measures; TCO – the total cost of ownership of an EV compared to the TCO of an internal combustion engine vehicle.

2.2. Phase 2 methodology

The methodology for Phase 2 is based on statistical data on the diesel and petrol consumption of the existing fleet. The data was taken from the Lithuanian Department of Statistics. It was assumed that EVs will be used at the same mileage as the current internal combustion engine vehicles.

$$EN = f\left(EV, FUEL\right), \quad (4)$$

where EN – the energy demand for electric vehicles in the EV fleet size scenario; $FUEL$ – fuel converted to the mileage of the existing fleet; EV – the size of the electric vehicle fleet.

The same equation was used for all three scenarios accordingly. Conversion coefficient is presented in Table 2.

Table 2. Conversion coefficient for energy (source: International standardisation organisation)

Energy in TJ	Litters of fuel
1 TJ	26 113,35 litter of diesel
1 TJ	29 824,75 litter of gasoline
1 TJ	40 000 litter of liquid petroleum gas

2.3. Phase 3 methodology

An interview programme was carried out to estimate the most appropriate technical solution and the power needs of the electric charging stations. The respondents were selected to represent the EV user associations and charging station manufacturers.

Three user groups were identified: private persons who will use electricity directly from an electric socket without a charging station; private persons who will use 11 kW charging stations; corporate users who are expected to use between 22 kW and 150 kW; and public stations using between 22 kw and 150 kW.

$$CS = f\left(USER, EN, D, U\right), \tag{5}$$

where CS – the number of charging stations; $USER$ – the type of user; EN – the amount of electricity needed for charging per year; D – the average time taken to fully charge a battery according to the average battery in each vehicle class; U – the charging station utilisation coefficient. The coefficient calculates the convenient number of hours per day to use a charging station. This coefficient is needed for public stations in order to estimate the capacity of the network.

The same equation was used for all three scenarios accordingly.

2.4. Methodology of phase 4 and 5

The methodology for phases 4 and 5 is very similar. Given the number of charging stations in phase 3, there follows a simple multiplication of the cost for each type of electric charging station (for phase 5). For phase 4, historical statistical data on the cost of installing a charging station incurred by a low-voltage grid operator were used, depending on the type of station.

$$I = f\left(CS, C_{Gr}, C_{St}\right), \tag{6}$$

where I – the investment needed for charging stations and grid upgrades; C_{Gr} – the grid investment needed per charging station, depending on the power; C_{St} – the cost of installing a charging station, depending on the power, including the cost of equipment and installation process.

The same equation was used for all three scenarios accordingly.

3. Results of forecasting

The three scenarios are named STAT, MEAS and GOAL. The STAT scenario represents a forecast based on regression analysis, while the GOAL scenario represents the pathway towards achieving the midterm (year 2025) and 2030 results per the national legislation targets. The MEAS scenario is based on modelling the effects of the planned measures.

3.1. Forecast of EV

The forecasting results of the STAT scenario are very modest compared to the MEAS and GOAL scenarios (Figure 1). In the M1 class of personal cars, the number of registered vehicles amounts to 1.59 million vehicles in Lithuania. It is forecasted to reach 1.65 million in 2030, of which 24.54 thousand will be BEVs or PHEVs in the STAT scenario. The calculations show that if the expansion of EVs were based solely on GDP and income growth, it would fall far below the official national targets. If all the measures that are planned by the central and municipal governments are implemented on time, to the right extent and scope, 210.57 thousand EVs are expected in 2030. However, the national legislation has set an estimated target of 284.88 thousand EVs by 2030. Accordingly, the government needs to take additional measures to ensure that at least 74 thousand EVs are available additionally by 2030.

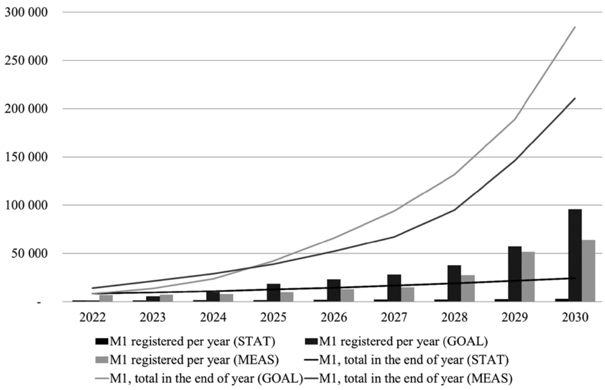

Figure 1. M1 EV forecast based on 3 scenarios (source: authors' calculation)

In the light commercial vehicle segment (Figure 2), which is typically used by utility companies, SMEs or small private businesses, the difference across all scenarios is much greater. There are 67.7 thousand N1 vehicles in 2021 and the number is expected to be 70.8 thousand in 2030, of which 960 are EVs in the STAT scenario, 29.8 thousand in the GOAL scenario, and 44.6 thousand in the MEAS scenario.

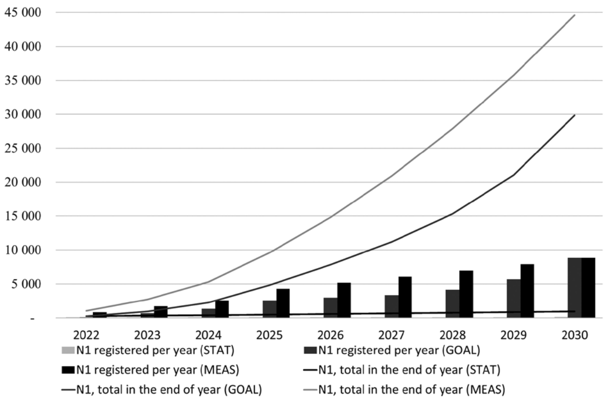

Figure 2. N1 EV forecast based on 3 scenarios (source: authors' calculation)

Figure 3 shows the trends in the M2 segment, which corresponds to light buses typically used in urban areas for shorter commutes or even transport on demand. It is expected to grow 121 times in the GOAL scenario and 95 times in the MEAS scenario, while the STAT scenario predicts only a 6-fold growth compared to 2022.

Figure 4 represents the forecast for light freight vehicles. In this segment, the future trends in the STAT scenario are quite promising compared to M2. Moreover, the planned measures in the N2 segment lead to greater growth than the GOAL scenario. In the MEAS scenario, the number is expected to reach 1325 M2 vehicles by 2030.

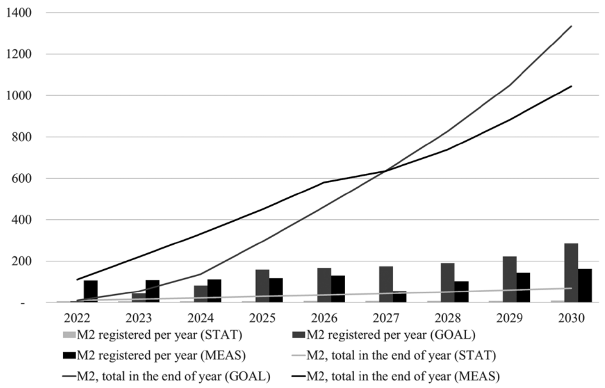

Figure 3. M2 EV forecast based on 3 scenarios (source: authors' calculation)

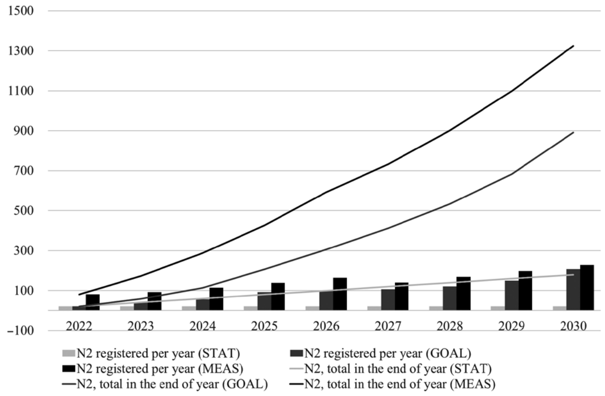

Figure 4. N2 EV forecast based on 3 scenarios (source: authors' calculation)

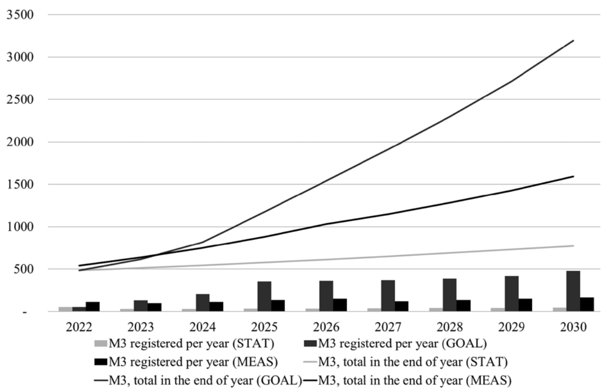

Figure 5. M3 EV forecast based on 3 scenarios (source: authors' calculation)

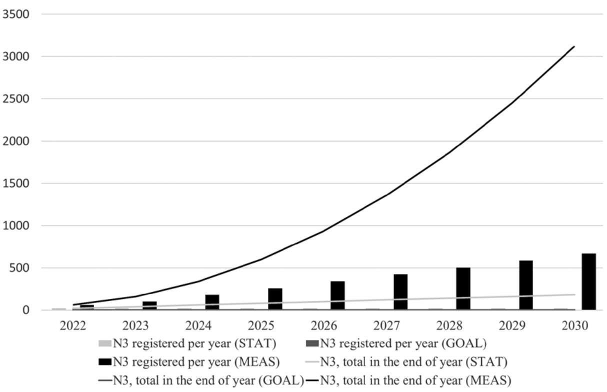

Figure 6. N3 EV forecast based on 3 scenarios (source: authors' calculation)

The M3 segment, namely buses used for daily urban public transport and intercity connections, is presented in Figure 5. The forecast shows that the measures planned by the government are not sufficient to reach the national target and that additional measures need to be introduced in 2025 at the latest.

he forecast for the heavy lorries segment is presented in Figure 6. The GOAL scenario for this segment differs significantly from the other scenarios because the Lithuanian government does not set specific targets for the N3 segment in the national legislation. However, the measures that are planned for other vehicle segments will also affect the N3 segment, especially the restrictions on access to the city centre for diesel and petrol vehicles.

Figures 7–9 represent the proportions of each vehicle type in the future trends in all three scenarios. In 2030, personal vehicles (M1) are forecasted to account for 91.9 percent of the EV fleet in the STAT scenario, 89.0 percent in the GOAL scenario, and 80.3 percent in the MEAS scenario.

Based on the projected number of EVs in 2030, the general conclusion is that M1 personal vehicles should be the main focus of energy consumption evaluation in all scenarios.

3.2. Forecast of energy consumption

Over the last decade, annual energy consumption in Lithuania has fluctuated between 11 and 13 TWh. By

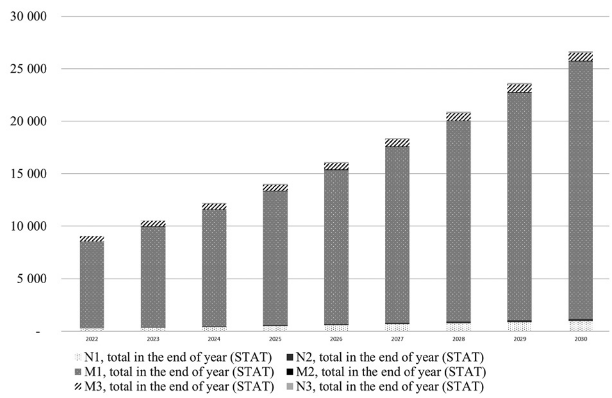

Figure 7. All types EV forecast based on STAT scenario (source: authors' calculation)

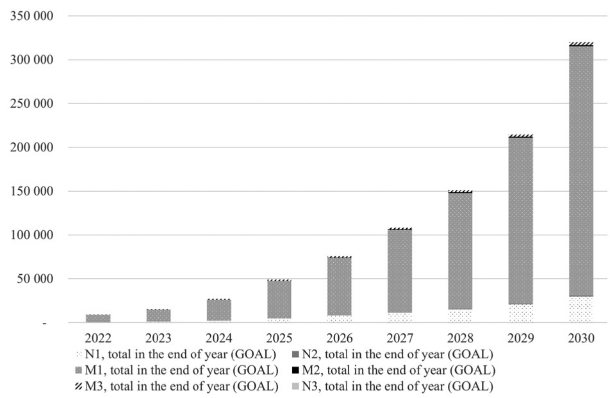

Figure 8. All types of EV forecast based on GOAL scenario (source: authors' calculation)

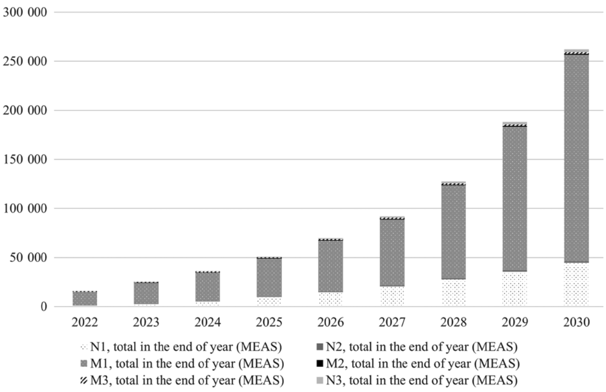

Figure 9. All types EV forecast based on MEAS scenario (source: authors' calculation)

forecasting the number of electric vehicles and estimating the energy usage for each vehicle type, it is possible to identify the future trends and the additional energy demand needed for electric vehicles by 2030 (Figure 10). In the STAT scenario, an additional energy demand of 134.8 GWh is expected by 2030, representing 1.0 to 2.6 percent of the total energy consumption in the country. The GOAL and MEAS scenarios show a very similar energy demand in 2030, with 1.09 TWh being the annual electricity consumption of EVs. This corresponds to between 8.4 and 9.9 percent of the total energy consumption in the country.

Figure 11 represents the main electricity consumers in the STAT scenario. M1 personal vehicles and M3 buses account for the largest part of electricity consumption at 107.4 GWh, or 79.6 percent of the total electricity consumption by EVs in 2030.

Figure 12 represents the main electricity consumers in the GOAL scenario. M1 personal vehicles are the largest electricity consumers at 686.9 GWh, or 63.0 percent of the total electricity consumption by EVs in 2030.

Figure 13 represents the main electricity consumers in the MEAS scenario. M1 personal vehicles account for the largest part of electricity consumption at 507.7 GWh, or 46.5 percent of the total electricity consumption by EVs in 2030.

Based on the overall trends in EV energy consumption, the general conclusion is that private cars are expected to be the main electricity consumer. Therefore, it is important to estimate the need for the deployment of charging stations with a focus on private users.

3.3. Forecast of charging stations

The annual number of charging stations is presented in Figures 14–16.

At least 8213 charging stations are needed by 2030 to meet the demand of M1 EVs – even in the STAT scenario.

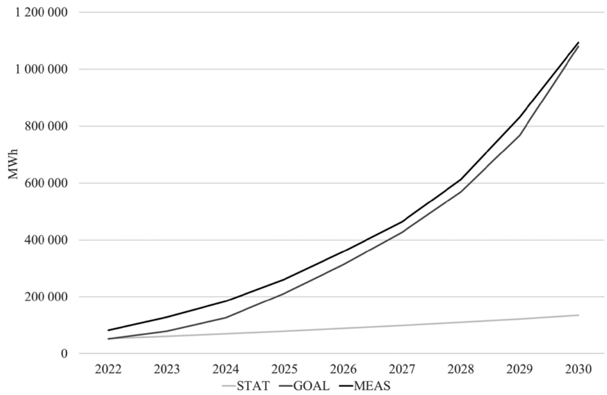

Figure 10. Annual energy consumption by EV forecast based on 3 scenarios

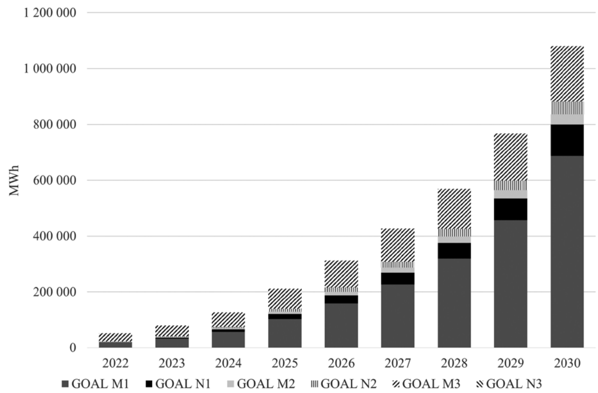

Figure 12. Annual energy consumption by EV forecast based on GOAL scenario (source: authors' calculation)

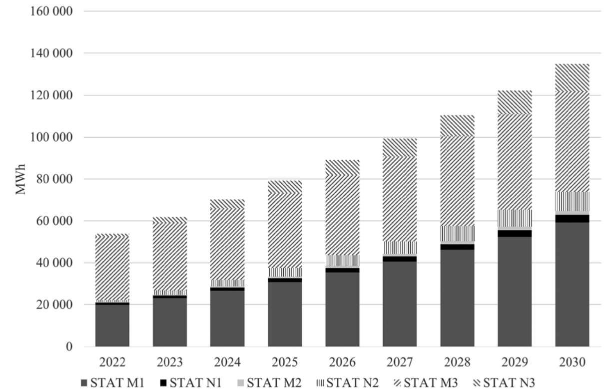

Figure 11. Annual energy consumption by EV forecast based on STAT scenario (source: authors' calculation)

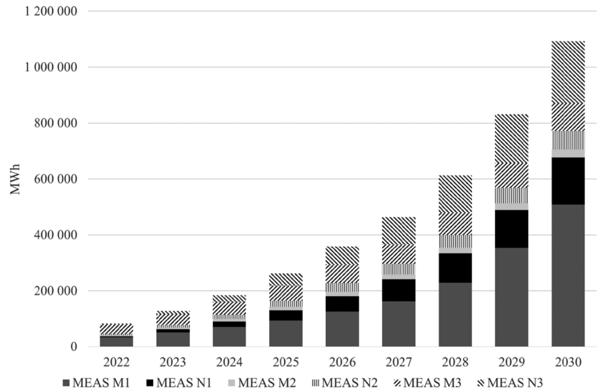

Figure 13. Annual energy consumption by EV forecast based on MEAS scenario (source: authors' calculation)

95.8 thousand home charging points are forecasted in the GOAL scenario and 71.4 thousand in the MEAS scenario.

However, home charging stations alone are not enough to ensure an efficient EV charging network. The number of charging stations planned for corporate entities (businesses, office buildings, supermarkets) in 2030 is as follows: 6083 units (22 kW power) in the STAT scenario, 464 units (150 kW power) in the MEAS scenario; 6062 (22 kW) and 284 (150 kW) in the GOAL scenario.

In addition to private and corporate charging stations, the government needs to create a public network.

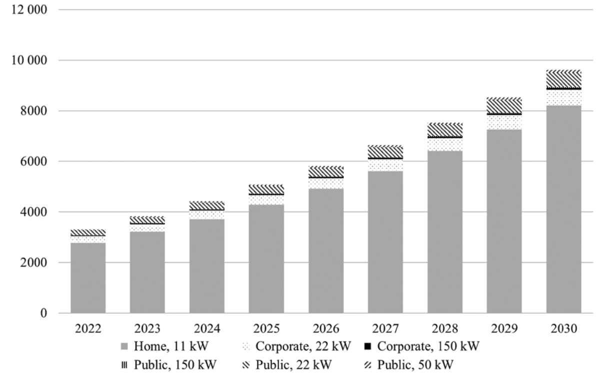

Figure 14. Annual charging station forecast based on STAT scenario (source: authors' calculation)

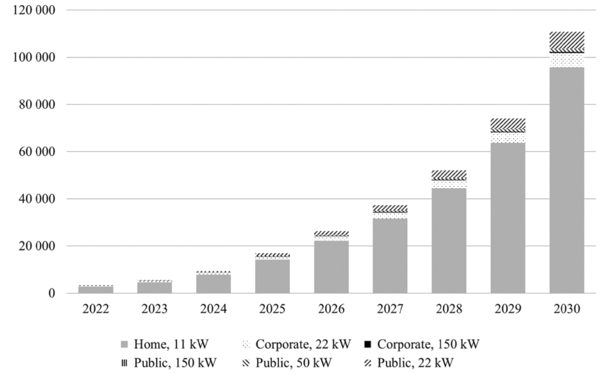

Figure 15. Annual charging station forecast based on the GOAL scenario (source: authors' calculation)

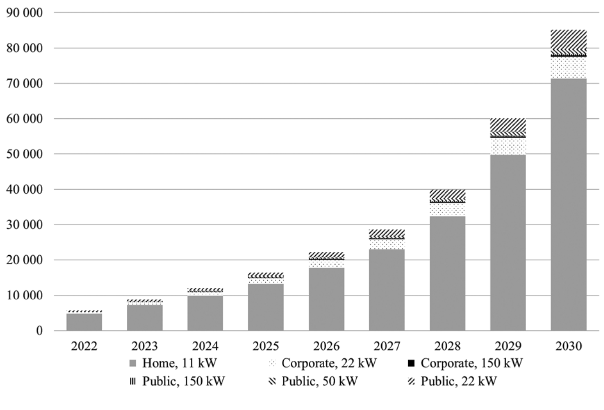

Figure 16. Annual charging station forecast based on MEAS scenario (source: authors' calculation)

In the STAT scenario, it is estimated that a network of 717 charging stations would meet consumer demand by 2030. In the GOAL scenario, many more public charging stations will be necessary by 2030: 7049 (22 kW), 1463 (50 kW) and 94 (150 kW). In the MEAS scenario, the figures are as follows: 5486 (22 kW), 1446 (50 kW) and 253 (150 kW) by 2030.

3.4. Forecast of investments

Taking into account the number of different types of charging stations and the various infrastructure and installation costs, the total amount needed to upgrade the low-voltage electricity grid is estimated at EUR 230.0 million in the GOAL scenario and EUR 192.4 million in the MEAS scenario (Figure 17).

Taking into account the number of different types of charging stations and the various infrastructure and installation costs, the biggest investment by 2030 (Figure 18) is expected to be EUR 102.5 million for private users (GOAL scenario), EUR 85.2 million for public users (GOAL scenario), and EUR 41.48 million for corporate users (MEAS scenario).

The overall conclusion of the chapter emphasises the importance of private investment in charging stations and the role of the low-voltage grid operator in investing in grid upgrades.

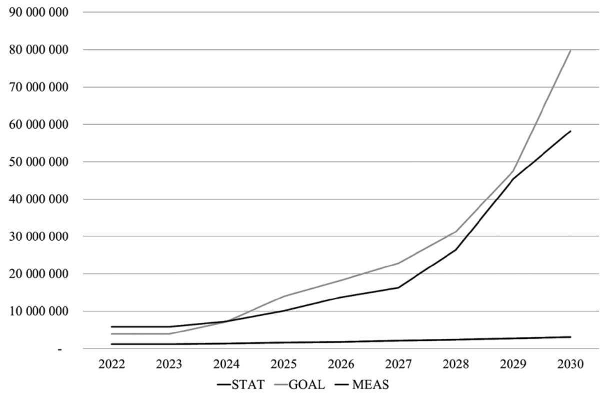

Figure 17. Annual investment demand forecast to upgrade electricity distribution grid based on 3 scenarios (source: authors' calculation)

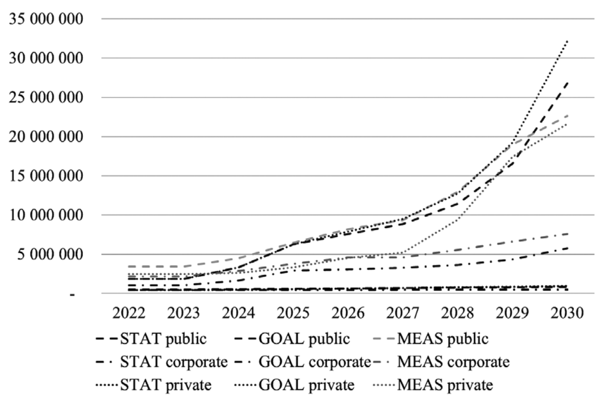

Figure 18. Annual investment demand forecast to build charging stations based on 3 scenarios (source: authors' calculation)

Conclusions

The European Green Deal (European Commission, 2019b) has inspired a number of research activities around the world to predict future trends. An analysis of recent scientific work shows that future forecasts are still uncertain due to the differences in countries' economic, legal and even cultural behaviour. There is still a lack of a single recognised model to predict EV future trends and a lack of investment to support these trends. Important findings from literature analysis come that various policy measures, such as subsidies, tax discounts, zero emission zones are contributing to the growth of electric vehicle fleet significantly. So, it justifies why the MEAS scenario in the Lithuanian case is so different from the STAT scenario. Moreover, it justifies, why MEAS and GOAL trends are so close if Lithuanian case.

The analysis of the Lithuanian case, expressed in three scenarios, focuses on two trends. One trend is very modest, based on purely statistical extrapolation and a multicriteria analysis of past trends, using a regression method. The statistical scenario, which is based on the forecasts of economic growth, purchasing power and GDP, shows that there will be 26.7 thousand EVs in Lithuania in 2030 (compared to 7750 in November 2021). Therefore, the minimum expected growth over 8 years should be 347 percent. This scenario requires EUR 3.0 million investment in the low-voltage grid and EUR 2.3 million investment in charging stations. In 2030, an additional 134.8 GWh of electricity will be needed, representing between 1.0 and 2.6 percent of the total national electricity consumption.

The national legislation targets scenario (GOAL) and the planned measures scenario (MEAS) are very similar. The GOAL scenario projects 319 470 EVs and the MEAS scenario projects 262 247 EVs. Both scenarios create a demand for 1.09 TWh of electricity, representing 8.4–9.9 percent of the total energy consumption in the country.

Both scenarios create a demand for a total investment of EUR 192.5 million and EUR 230.0 million in the low-voltage grid in the MEAS and GOAL scenarios, respectively.

Both scenarios create a demand for a total investment of EUR 204.2 million and EUR 209.0 million in the charging stations in the MEAS and GOAL scenarios, respectively. The total accumulated investment need by 2030 is between EUR 396.7 million and EUR 439.0 million to support either the MEAS or GOAL scenario.

The major added value of the research paper is oriented towards policy makers and specialists responsible for country-wide capacity of electricity distribution network. In the coming 3 years, the monitoring of EV trends is needed to verify realisations of scenario. Significant difference among scenarios will come in year 2025.

Disclosure statement

Authors declare that they have any competing financial, professional, or personal interests from other parties on results of research.

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