DEVELOPMENT OF ELECTRIC ROAD TRANSPORT: SIMULATION MODELLING

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Electric transport is rapidly gaining popularity across the world. It is an example of technological advancement that has multiple consequences for regional economies, both in terms of the adaptation of production, transport and energy systems and their spatial optimization. The experience of leading economic regions, including countries of the Baltic Sea region, shows that electric transport can potentially substitute traditional transport technologies. Based on an authentic model of system dynamics, the authors propose a new approach to simulation modelling of the dissemination of electric vehicles in a given region. The proposed model allows the authors to take into account the key systemic feedback loops between the pool of electric vehicles and the charging infrastructure. In the absence of data required for the econometric methods of demand forecasting, the proposed model can be used for the identification of policies stimulating the consumer demand for electric vehicles in regions and facilitating the development of the electric transport infrastructure. The proposed model has been tested using real and simulated data for the Kaliningrad region, which due to its specific geographical location, is a convenient test-bed for developing simulation models of a regional scale. The proposed simulation model was built via the AnyLogic software. The authors explored the capacity of the model, its assumptions, further development and application. The proposed approach to demand forecasting can be further applied for building hybrid models that include elements of agent modelling and spatial optimization.

Keywords:
simulation modelling, system dynamics, electric transport, electric vehicles, charging stations infrastructure, region, demand forecasting, demand stimulation, Bass model, AnyLogic

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Introduction

The past 10 years have seen a rapid expansion of electric transport. At the end of 2018, there were over 5 million electric cars in the world.[1] Forecasts say that in 10 years, by 2030, one-third of all cars sold will use an electric motor. This was made possible by advances in rechargeable battery technologies, primarily lithium-ion ones [1].

Individual vehicles with electric traction motor are a natural substitute for transport powered by internal combustion engines (ICE). The former are known to have technological advantages (if used) in terms of operating costs, environmental friendliness, and ease of maintenance [2].

Given the current level of technology development, individual electric vehicles (EVs) have some drawbacks. For the most part, these are difficulties associated with the operation of lithium-ion batteries in cold climates.[2] It is a clear example of the regional factor influencing the spread of electric vehicles.

The literature examines a considerable number of new academic and practical issues around EV adoption dynamics [3—8]. This paper concentrates on the problem of reaching the *critical mass* for the new technology to spread in a particular region, specifically, it analyses the necessary conditions for the irreversible spread of individual EVs at the regional level. The study aims to track the dynamics of EV adoption in the Kaliningrad region, taking into account the purchasing power of its residents.

The focus is on the regional dimension of the topic since the development of electric transport is critically dependent on regional factors and has a systemic effect on the development of the territory. These factors include regional climatic and socio-demographic characteristics, as well as the associated parameters of energy and transport networks, the structure of utility services, etc. As a result, projections of electric vehicle take-up are regionally specific.

This study is of practical significance as it provides a methodological approach to forecasting the development of electric transport systems when the data are insufficient for econometric modelling. This is achieved using an original system dynamics simulation model with tools based on the numerical solution of systems of first-order differential equations.

The subject of the study is the *creation of a model for assessing and scenario-based forecasting of the influence of key factors on electric transport adoption*

[1] *IEA* (2018). Global EV Outlook 2018: Towards cross-modal electrification. OECD/ International Energy Agency. URL: https://www.connaissancedesenergies.org/sites/default/files/pdf-actualites/globalevoutlook2018.pdf (accessed: 30.12.2019); *IEA* (2019). Global EV Outlook 2019: Scaling-up the transition to electric mobility. International Energy Agency. URL: https://www.iea.org/reports/global-ev-outlook-2019 (accessed: 30.12.2019).

[2] Other disadvantages, such as the relatively short mileage per charge, are quickly removed with the development of technology. It is believed that by 2023—2025, there will be parity between EVs and ICE cars.

in the region. The problems addressed by the modelling framework include the assessment of electric vehicle take-up in a region under various scenarios depending on 1) the development of charging infrastructure, 2) the initial public contract, and 3) the amount of subsidy for an EV purchase. The model is unique as it provides in-depth analysis of regional specifics determining the modelling context and uses special stream model representations, in particular, an original approach to modelling the state of consumer choice and the factors influencing it.

The model is to answer the following questions.

What amount of subsidy can drive the decision to purchase an electric vehicle?

What minimum level of charging infrastructure can encourage the abandonment of ICE cars in favour of electric vehicles?

What is the minimum electric vehicle fleet to foster the development of a network of private charging stations?

The model can be useful for decision-makers on EV incentive policy, experts in market analysis and diffusion of innovations (in this case, EVs), as well as a wide range of people interested in the accurate forecast for the Russian EV market development.

The Kaliningrad region was chosen as a pilot region for the study.

The rest of the paper is structured as follows. First, we consider the trends in EV adoption in the world, including the countries of the Baltic Sea region. This is followed by a more detailed description of the fleet of the Kaliningrad region, accompanied by a parallel discussion of the features and deficiencies of modelling the development of electric vehicles and charging infrastructure with only limited observational data available. Then follows a description of a simulation-based approach that takes into account feedback links between the electric vehicle fleet and the charging infrastructure. The AnyLogic PLE software package is used to implement the system dynamics model [9—11]. The test data come from the Kaliningrad region, whose unique exclave position and compact key subsystems make it ideal for regional simulation models [12]. That is why it can serve as a pilot region for testing policies for the promotion of electric vehicles in Russian regions. Our study relies on estimates based on statistics on individual and commercial vehicles in the Kaliningrad region (according to the Avtostat database), as well as on scenario-based approaches to modelling demand-boosting tools (such as electric vehicle purchase incentives and charging infrastructure development [13; 14]). The final sections of the work are the analysis of the obtained results and the discussion of further research.

Global and BSR electric vehicle trends

Electrical vehicles are growing in popularity. According to leading world experts, by 2030 up to 20-30% of the fleet of developed countries will be electric. In some states, for example, Norway, which is the leader in terms of private electric car proportion, EVs accounted for as much as 46% of the market at the end of 2018.[3]

The development of the global electric fleet (BEV and PHEV) is closely linked to the development of public charging infrastructure (Fig. 1).

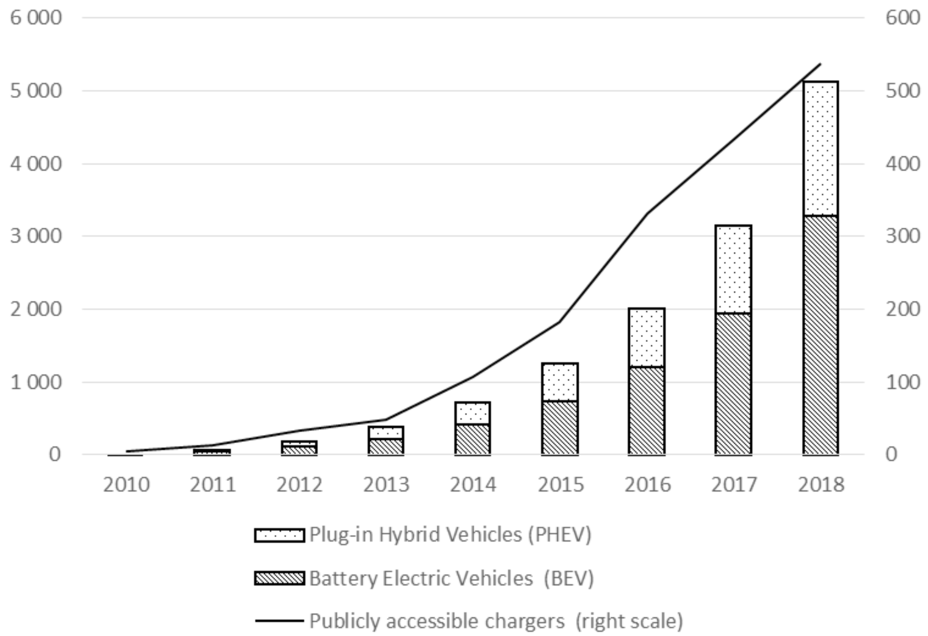


Fig. 1. The global electric vehicle fleet and public charging infrastructure development in 2010—2018 (left scale — thousand cars, right scale — thousand stations)

Sources: IEA (2019), authors' calculations.

Electric vehicle adoption in Russia is lagging behind the US, China and the leading EU countries. For instance, at the end of 2019, there were about 4.8 thousand electric vehicles in Russia. According to industry experts, by 2025, the share of electric car sales will not exceed 0.6% or 15,000 units.[4] To put that into perspective, China, the EU and the US, the world leaders in terms of electric vehicles adoption, accounted for 45%, 24%, and 22% respectively of the global EV market of 5.1 million cars in 2018. In 2013—2019, global EV sales were growing by more than 50% annually. According to IEA forecasts, by 2030 the global EV market will be 130—250 million units. In 10 years, EVs can account for up to 70% of all new vehicle sales in China, up to 50% in the EU, 37% in Japan, and more than 30% in the US and Canada.[5]

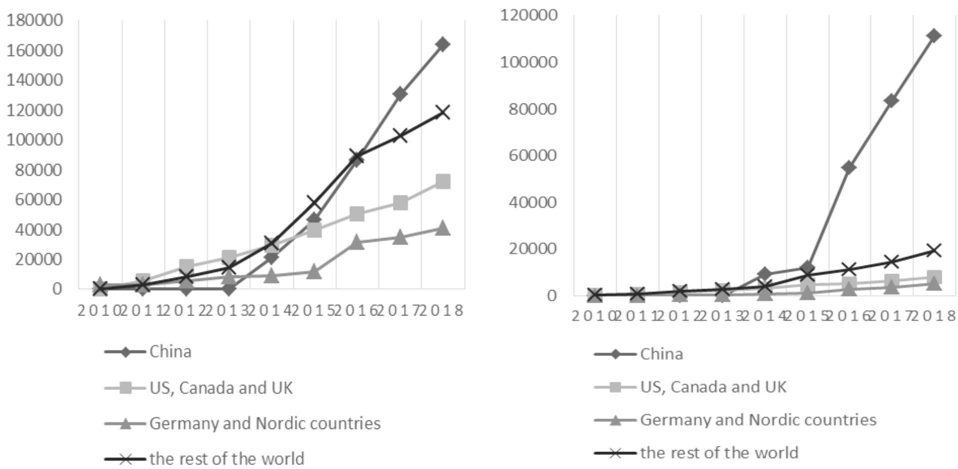
[3] *IEA* (2019).

[4] Overview of the Russian automotive market in the 1st half of 2019 and development prospects. Special issue: electric cars. p. 10 (in Russ.). URL: https://www.pwc.ru/ru/materials/pwc-auto-press-briefing-2019.pdf (accessed: 01.12.2020).

[5] *IEA* (2019).

Traditional factors limiting consumer demand for electric cars include long charging time, low mileage on a single charge, high price, and underdeveloped charging infrastructure. Over the past five years, however, rapid technological advances have weakened the constraints if not removed them entirely.

According to observations, there is a fairly stable ratio requirement for the full development of EVs: there should be at least one public charging station for every



a) slow charging stations b) fast charging stations

Fig. 2. Distribution of public charging stations in the world in 2010—2018, units

Sources: IEA (2019), authors' calculations.

10 electric cars.[6] At the same time, charging infrastructure development should be somewhat advanced to reach a critical mass of vehicles. Besides, each electric car should have an individual spot for overnight charging. These technological requirements underpin various strategies for developing charging infrastructure in different regions. As Figure 2 shows, China is the world leader in terms of the number of charging stations; it relies mainly on fast charging (Fig. 2b)[7].

Experts predict a single-charge mileage of 400 miles (~ 644 km) in five years. This will significantly increase long-distance travel and demand for public charging stations [15].

[6] *IEA* (2019).

[7] Note that most public charging stations are considered slow, as they are designed for power output of up to about 20 kW per car. Thus, it takes one hour to charge a car to 20 kWh (while most cars are still oriented to a battery capacity of about 40 kWh). It is believed that fast charging stations can produce 50 or more kW per car, thereby reducing charging time by 2.5 or more. Technologies are developing very quickly: super-fast stations can produce 150 kW or more per vehicle. So far most batteries (and charge management systems are not fit for such power. In 10 years, the situation can change dramatically, and there can be a sharp increase in the number of electric vehicles.

The world leader in the number of electric cars per capita, Norway, is focusing on slow charging infrastructure. This is probably due to the housing structure, where most households have individual houses (only about ¼ of households live in large apartment buildings).[8] Infrastructure optimisation depends on the cost of electricity in the region, the existing energy networks, and the technological possibilities to connect new charging stations to the grid, as well as on their spatial distribution. Research has shown that, in the US, fast charging public stations become competitive with home charging at the utilisation rate of 20%, whereas the 2018 average was about 5% [15].

The following section gives an overview of the Kaliningrad regional automotive market.

Road transport in the Kaliningrad region: input data

Several factors appear to favour the launch of the pilot project on promoting EV adoption in the Kaliningrad region:

1) convenient geographical location — the Kaliningrad region borders on two EU countries (Poland, Lithuania) which are actively developing electric transport and networks of charging stations;

2) the relatively small size of the region — its maxim um length from west to east is 205 km, from north to south, 108 km; this makes EV travel within the region efficient since a modern electric car can travel up to 250-400 km on a single charge;

3) capabilities to localise the manufacturing of electric vehicles, their components and elements of charging infrastructure, both on a regional and national scale;

4) favourable socio-demographic characteristics — the population of the region is 1.022 million people, of which 622.4 thousand people are of working age and 527.5 thousand people are economically active (statistics indicate an employment rate of 67.1 % in 2017)[9];

5) transparency of the regional energy network.

Our study focuses on the passenger car segment, as the development of commercial and public transport is highly distinctive. Nevertheless, in terms of state support the public transport fleet has an advantage as the charging infrastructure is primarily concentrated around depots and along the main routes.

Table 1 presents vehicle distribution by type in the Kaliningrad region to provide a comprehensive picture.

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[8] Detailed statistics are available at: *Dwellings*. Statistics Norway. URL: https://www.ssb.no/en/boligstat (accessed: 01.16.2020).

[9] Forecast of labour resources balance in Kaliningrad region for 2018-2020 (in Russ.). URL: https://gov39.ru/biznesu/zanyatost/prognoz_balansa.php (accessed: 01.15.2020).

Table 1

Distribution of vehicles by type in the Kaliningrad region, thousand units

Vehicle type	Number	Share, %
Private cars (PC)	359	75.3
Light commercial vehicles (LCV)	54	11.3
Medium and heavy commercial vehicles (M and HCV)	28	5.9
Transport vehicles, excluding LCV	3	0.6
Others (motor vehicles, trailers, etc.)	33	6.9
Total	477	100.0

Sources: Avtostat database, authors' calculations.

The structure of the car park of the Kaliningrad region is the legacy of the early 1990s and the then active imports of used vehicles from Europe. Consumer behaviour has changed nevertheless. This shows in the country-of-origin shifts (Table 2).

Table 2

The passenger car fleet of the Kaliningrad region by age and country of origin[10] at the end of the 1st quarter of 2019, units/%

Country	Before 1991	1991—2000	2001—2010	2011—2019*	Total*
Germany	72.065/20.1	46.516/12.9	27.578/7.7	14.372/4.0	160.531/44.7
Japan	9.817/2.7	16.826/4.7	33.586/9.3	18.345/5.1	78.574/21.9
France	2.607/0.7	6.159/1.7	13.079/3.6	7.974/2.2	29.819/8.3
US	7.855/2.2	5.922/1.6	10.424/2.9	3.886/1.1	28.087/7.8
South Korea	47/0.0	1.170/0.3	9.119/2.5	17.199/4.8	27.535/7.7
Russia	4.415/1.2	3.132/0.9	4.038/1.1	2.828/0.8	14.413/4.0
Czech Republic	17/0.0	886/0.2	3.027/0.8	5.586/1.6	9.516/2.6
Sweden	1.435/0.4	626/0.2	958/0.3	277/0.1	3.296/0.9
Italy	1.066/0.3	706/0.2	480/0.1	31/0.0	2.283/0.6
UK	68/0.0	594/0.2	671/0.2	382/0.1	1.715/0.5
China	0/0.0	0/0.0	396/0.1	1.271/0.4	1.667/0.5
Others	498/0.1	724/0.2	446/0.1	110/0.0	1.778/0.5
Total	99.890/27.8	83.261/23.2	103.802/28.9	72.261/20.1	35.9214/100.0

Sources: Avtostat database, authors' calculations.

Note: * — at the end of the 1st quarter of 2019. About 10.2 thousand cars (2.9% of the total) belong to legal entities.

[10] The 'country of origin' is often different from the 'country of manufacture'. This research uses the 'country of origin of the brand' parameter, as it has a greater impact on consumer preferences.

The increase in the share of new cars purchased by households is associated with a growth in the share of Korean and Czech cars, which are driving German and Japanese models out of the market (Fig. 3). Petrol cars account for 83.3% of the fleet; 16.4% are diesel cars; the rest are hybrid, 85% of them produced in 2007—2011. On mid-2019, there were about 800 hybrid and 10 all-electric cars registered in the Kaliningrad region. This indicates that even in an underdeveloped EV environment innovators are willing to try novel products.

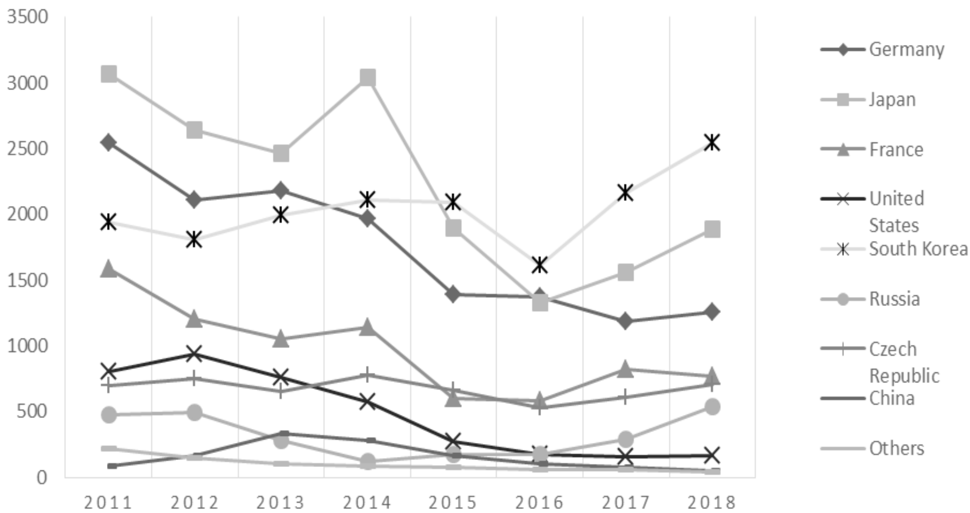

Fig. 3. The structure of the fleet of cars produced in 2011—2018 by country of origin in the Kaliningrad region

Sources: Autostat database, authors' calculations.

Nevertheless, the number of electric vehicles is still insufficient to apply discrete choice methods used in the theory of industrial organisation for demand analysis [16]. Naturally, in countries with the more rapid development of electric transport, there have been attempts to forecast demand by econometric methods [17]. Their use is, however, limited by both data scarcity and the specificity of the simulated situation. This is because the current versions of mixed logit models for discrete choice [18, pp. 955—970], originating from the BLP model [19], are difficult to adapt to the situation when a fundamentally different alternative is added to existing products on the market. In such cases, simulation methods, including agent-based models, system dynamics models, and their combinations, come to the forefront.

Until 2025, small cars will dominate the EV market. After 2025, we can expect the batteries' development level to be sufficient to ensure their efficiency in larger vehicle segments. This gives importance to the fact that compact cars account for at least 35% of the total fleet (Tab. 3).

Table 3

Consumer preferences by car category and body style in the Kaliningrad region, as a percentage of the total fleet

Type	Saloon	Estate	Hatchback	Others	Total
A	0.11	0.03	2.03	0.02	2.19
B	7.46	0.75	6.14	1.26	15.62
C	6.55	1.87	9.55	2.01	19.98
D	15.59	5.02	0.41	2.91	23.93
E	8.55	1.38	0.05	0.63	10.61
MPV	0.01	4.04	0.83	0.00	4.88
SUV	0.01	15.96	0.85	0.16	16.98
Other	1.82	0.72	0.37	2.90	5.81
Total	40.10	29.78	20.23	9.89	100.00

Sources: Avtostat database, authors' calculations.

Note: the broad categories are those used in the Avtostat database. MPV stands for Multi-Purpose Vehicle; SUV for Sport-Utility vehicle.

Our analysis makes it possible to estimate prospective EV demand to construct scenarios of the proposed system dynamics simulation model. The applied system-dynamic approach aids in implementing multivariate modelling of complex socio-economic systems taking into account non-linear feedback links [11; 20—22].

Model structure

The system dynamic model is based on a modified diffusion model of innovative products developed by Frank Bass [23; 24]. System dynamics is based on the interaction of stocks and flows (Fig. 4). Stocks represent the state of a particular variable at a given point in time, and flows represent the inflows or outflows of this variable over time. A key feature of system dynamics models is the possibility to model feedback effects (including those with delay function) between variables. The flexibility of the system dynamics approach providing for numerical modelling makes it possible to use arbitrary relations between variables and remove the requirement for a system to be analytically solvable. The modern trend in system dynamics suggests avoiding overly complex and detailed models reflecting only the most important properties of the simulated system [25; 26].

The classical F. Bass model holds that any market can be represented through at least two variables — the number of potential buyers and actual adopters [23]. The intensity of flows between them depends on a number of factors. We have modified the basic model to reflect the specifics of consumer decision-making when choosing between an ICE car and an EV. As indicated above, there is an active discussion around the simulation modelling of EV adoption in different regions of the world [27—33]. Features distinguishing the proposed model from others are the specifics of modelling the consumer decision-making on EV choice and the corresponding feedback structure. The simulation period is 120 time units (months). Figure 4 provides the general layout of the model.

The model consists of two main blocks:

1) ‘Consumer Choice’, or consumer decision-making block;

2) ‘Charging infrastructure’ block.

The ‘Consumer Choice’ block is a schematic diagram of choosing between ICEs and EVs. The ‘Potential buyers’ stock is further divided into ‘ICE car buyers’ and ‘EV buyers’, corresponding to the same-name stocks in Fig. 4. After a certain period (60 months, which is equivalent to the average length of car ownership), ‘ICE car buyers’ move to ‘Customers making a decision’ category (corresponding stock). Here, they can choose either an ICE car (returning to the ‘ICE car buyers’ stock) or an EV. The rationale for selecting an EV as a more attractive purchase option than a traditional car is based on the *Ratio of the subsidised EV price to the ICE car price*. The lower the subsidised price of the electric car compared to the ICE car, the higher the potential buyers’ interest in electric vehicles.

Figure 5 shows the price-based car preference curve based on our expert estimates. For example, if the average price of a subsidised EV is two-thirds that of an ICE car, 15% of buyers making a decision will choose an EV. If a subsidised EV is half the price of an ICE car, a little over 20% of buyers will opt for an electric car.

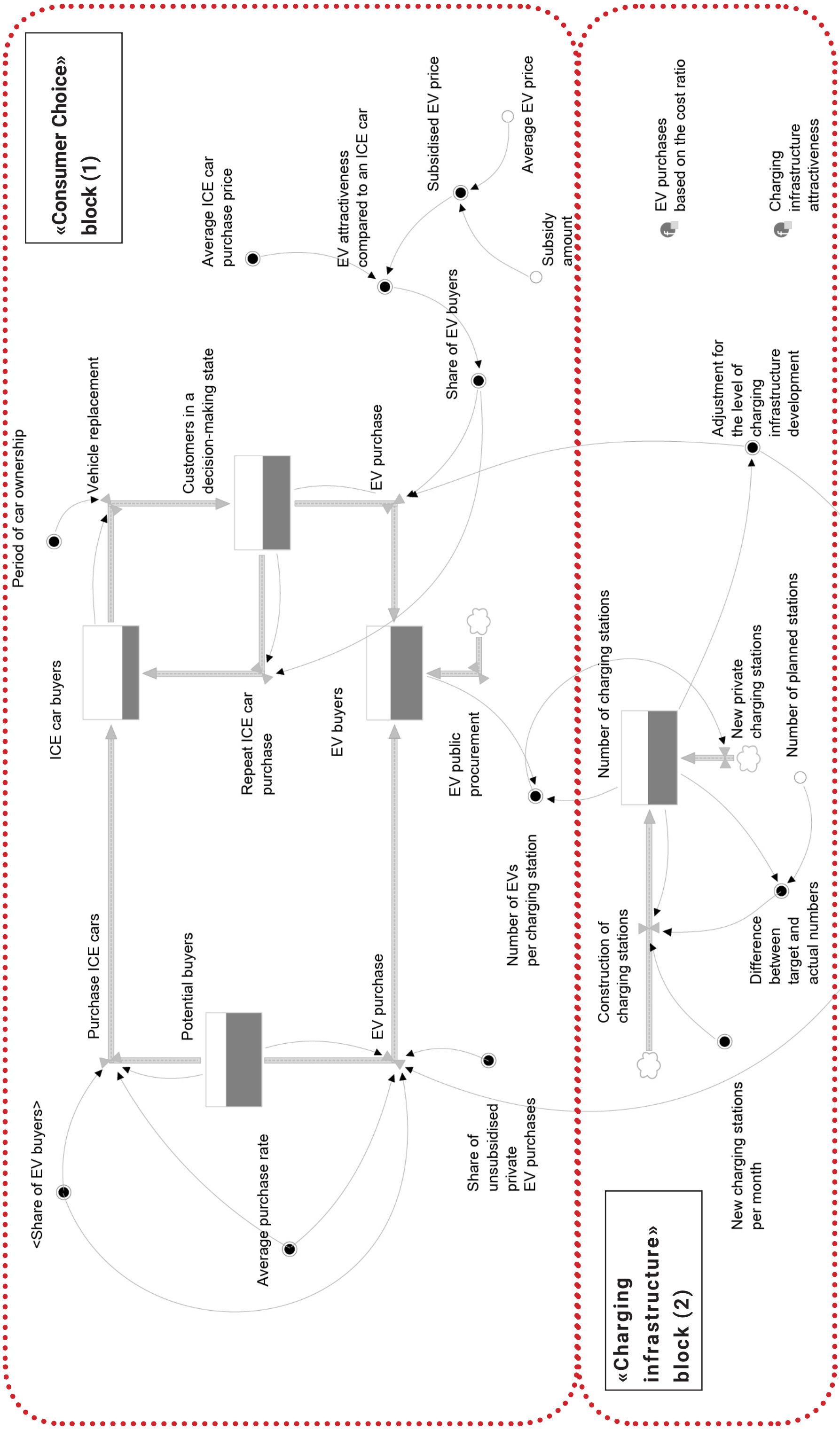

Fig. 4. Outline of the system-dynamic model

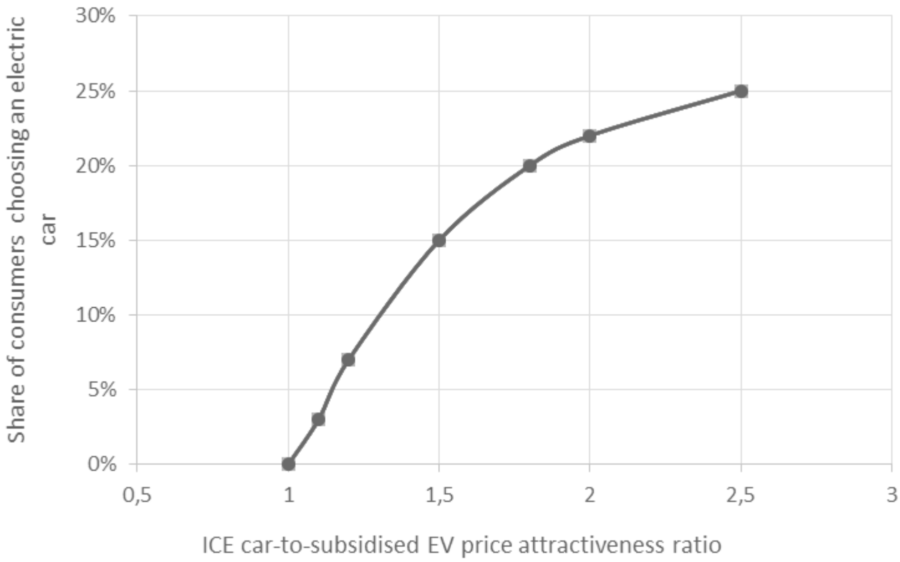

Fig. 5. Preference curve for EV buyers based on an ICE car to EV price ratio

Statistics show that an average of about 8 thousand cars is sold annually in the Kaliningrad region. About half of them are new cars sold on credit (4,194 cars in 2018).[11] In 2018, the average car loan amount was 883,000 roubles. If the loan is between 30 and 50% of the car cost, the projected value of a new car is 1.2—1.8 million roubles. A potential buyer compares the price of a subsidised EV and an ICE car. The subsidy is 20—50% of the electric car purchase price, which is consistent with international practice [14].

For demonstration purposes, we used a two-factor model for EV purchase decision-making process, taking into account (1) the EV purchase price and (2) the level of charging infrastructure development in the region. Both factors are of paramount importance. They present the minimum set of critically important characteristics for choosing an EV over an ICE car. The study uses a deliberately simplified model, avoiding its complication by secondary factors, thus leaving the area for subsequent research. Modelling even a relatively simple two-factor model for EV purchase decision-making is a non-trivial scientific task.

The development of the charging infrastructure is taken into account using the correction factor adjusting the number of people willing to purchase an electric car (Fig. 6). The factor is based on our expert estimates. It changes dynamically along with the development of the infrastructure in the region as the network of public charging stations grows. We assume that in the charging network the ratio of fast and superfast stations to slow stations is 1:4.

[11] Analysts: The demand for new cars in Kaliningrad is growing (in Russ.). URL: https://kaliningrad.rbc.ru/kaliningrad/12/02/2019/5c62a6949a7947df2c286878 (accessed: 20.01.2020).

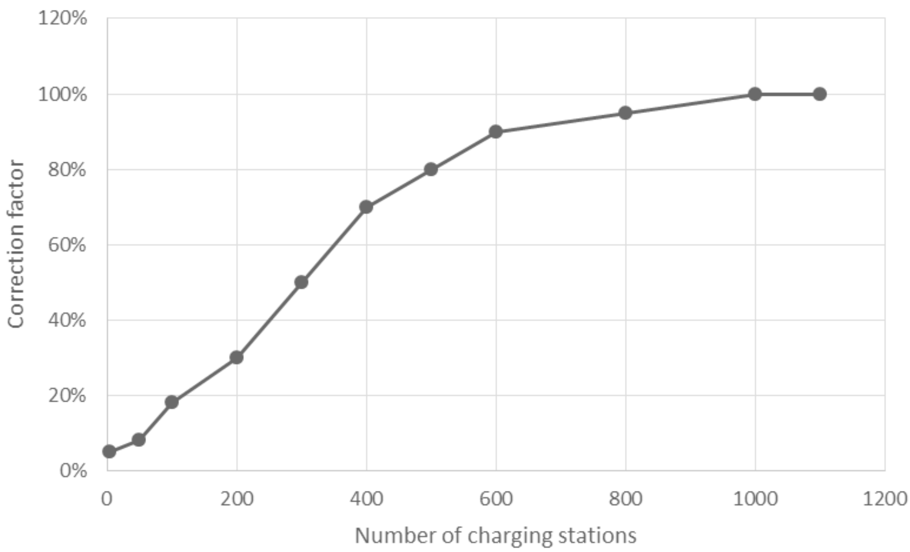

Fig. 6. Preference curve for EV buyers based on the availability of charging infrastructure

As the charging infrastructure develops, the correction factor increases from 5 to 100%. If there are at least 1,000 public charging stations in the region, the correction factor for the infrastructure is 1, meaning that all consumers opting for an EV purchase it. If the number of charging stations is 600, only 80% of potential buyers of an electric vehicle make a purchase.

Accordingly, the **'Charging Infrastructure' block** simulates the rate of new charging stations commissioning. We proceed from the assumption that the primary infrastructure of charging stations is set with state financial support, and with the increase in the EV number in the region, private investors gradually join in the development of charging infrastructure. As international researchers point out [33], the creation of the initial infrastructure of charging stations is critical to launching the electric vehicle sales cycle.

The charging infrastructure development is modelled using goal-seeking behaviour. The objective is adjusted in the model settings window (Figure 7). The target value of the number of charging stations is selected from a range of 200—1000 units. For simplicity of analysis, the number of stations under construction is calculated as a fixed proportion of the difference between the stations already built and those planned for construction (3%). The number of stations planned for construction is set by the *Number of planned stations* parameter.

There is also the *Number of EVs per charging station* parameter representing the ratio of the number of electric vehicles to the number of charging stations. The model uses the ratio of '10 EVs per public charging point', justified in *Global EV Outlook 2019*[12]. Since only a limited number of stations are state-financed, with an increase in EV purchases, the ratio grows. Thus as new charging stations, both state and privately financed, are commissioned, the *Number of EVs per charging station* parameter reaches the target value. Later, when the EV fleet grows and the parameter value falls, the cycle repeats. The model assumes that private investors set on average 15 stations per time unit until the parameter reaches its target value of '1 public station per 10 electric vehicles'.

Table 4 provides basic inputs and calculation prerequisites.

Table 4

Basic inputs

Variable	Value	Unit	Note
Modelling period	120	Months	—
Potential buyers	40,000	Buyers	Fixed parameter. Projected number of new car buyers in the Kaliningrad region over 10 years
Average monthly car purchase rate	1.65%	Share of total potential buyers	Fixed parameter. Monthly share of car buyers. Includes the number of EVs and ICE cars purchased
Average ICE car purchase price	1,200,000	Roubles / car	Fixed parameter
Average EV purchase price (unsubsidised)	1,700,000	Roubles / car	Fixed parameter
The number of state-financed charging stations	200—1000	Units	Variable parameter (see the 'Sensitivity analysis' section)
EV subsidy amount	30-50%	Percentage of EV price	Variable parameter (see the 'Sensitivity analysis' section)
Number of EVs per charging station (target value)	10	Units	Fixed parameter. If the ratio of EVs to charging station is higher, the option of privately-financed charging station construction is selected

[12] *EIA* (2019).

Figure 7 shows the results of the simulation experiment. If EV subsidy amounts to 50%, and there are at least 400 charging stations in the region, in 10 years the number of EV buyers will be approximately 5.7 thousand people (5,694). At the same time, the number of ICE buyers will be more than 28 thousand people (28,341). At the later model stages (after the first 60 months), there is a monthly average of about 50—60 EV and 500-520 ICE car purchases.

The total number of EV adopters in the entire period is 17%. Over 10 years, under the basic scenario, there are 514 charging stations commissioned, of which 400 are state-financed and 114 are privately financed (the 'Number of charging stations' in Figure 7). As the *number of EVs per charging station* grows exceeding the target value of 10 vehicles per station, the number of charging stations increases.

The simulation results generally correspond to the common European practice with EVs accounting for 5—15% of new car sales in 2019.[13]

Sensitivity Analysis

Simulation modelling has the advantage of running numerous experiments under easily altered scenarios. These scenarios are set by varying the most significant parameters in different combinations [11]. A sensitivity analysis of the model was performed on two key variables:

1) the number of public charging stations;

2) the necessary EV subsidy amount.

Figures 8 and 9 show the results of the sensitivity analysis on the number of charging stations. According to the calculations (Fig. 7), the total number of EV buyers varies significantly in the range of 200—600 stations, from 3,770 (200 stations) to 6,890 (600 stations). At the same time, the difference in the numbers of buyers between the network of 800 and 1000 stations is almost negligible. Thus, according to the calculations, taking into account the geographical and socio-demographic characteristics of the Kaliningrad region, a network of 600 charging stations will be generally sufficient for the successful development of electric transport on its territory.

[13] EIA (2019).

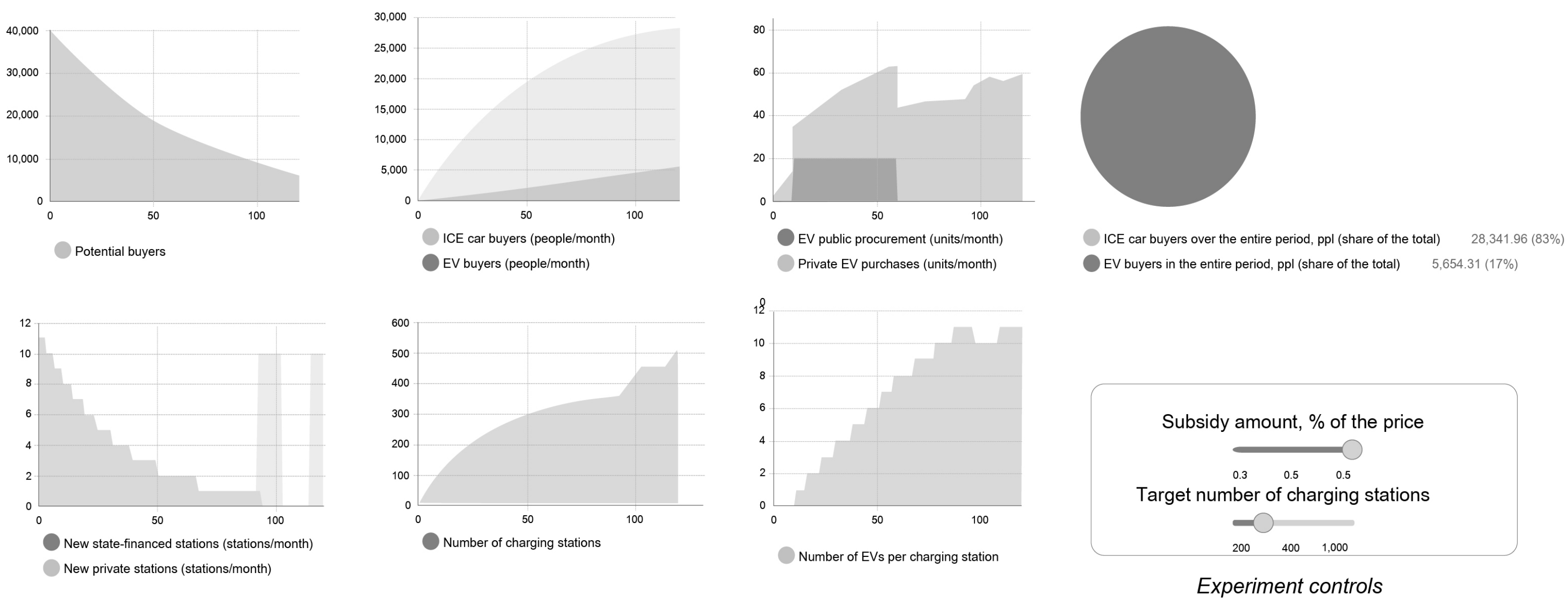

Fig. 7. Modelling results. Baseline scenario: a 50% subsidy for the purchase of an EV, state-financed construction of a network of 400 charging stations

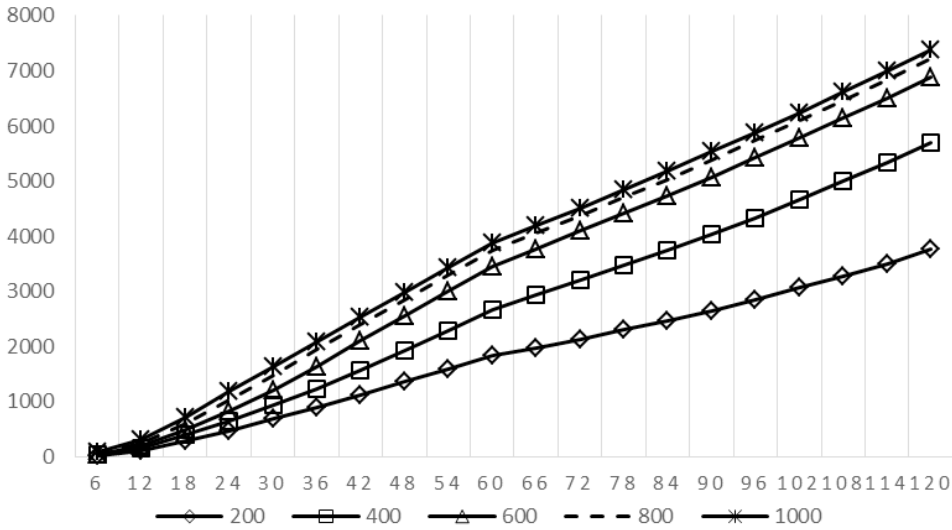

Fig. 8. Sensitivity analysis on the number of state-financed charging stations (range 200—1000 stations, increment — 200 stations): horizontal axis — time (120 months), vertical axis — the number of EV buyers (total) depending on the development of the charging infrastructure

Figure 9 shows the number of EV buyers per month depending on the subsidy amount. The results of the simulation experiment clearly show that the consumer's decision on EV purchase also largely depends on the government subsidisation of the EV price. The higher the subsidy (35—40% or more), the greater the number of EV buyers. The latter varies significantly in the 30—50% subsidy range. At a 50% subsidy, the number of buyers (7,490 people) is seven times that at a 30% subsidy (1,030 people). This result is largely based on the preference curve based on our analysis (Figure 5). Further market research validating the preference curve can substantially refine the simulation results.

Conclusion

The proposed system dynamics model made it possible to identify measures required to stimulate EV demand in a region with a low level of electric transport development.

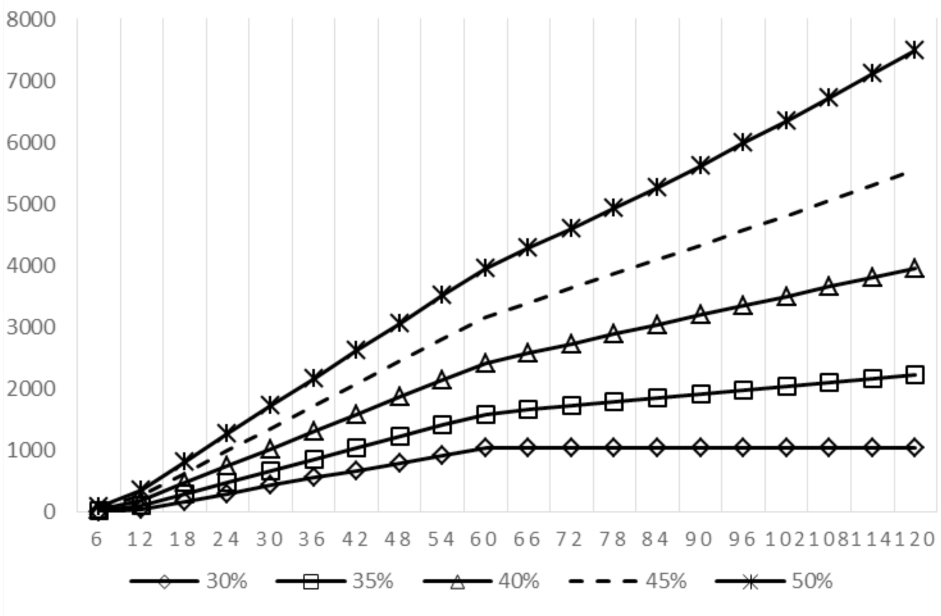

Fig. 9. Sensitivity analysis on the amount of subsidy for the purchase of an EV (range of subsidies of 30—50% of the EV cost, increment — 5%): horizontal axis — time (120 months), vertical axis — the number of EV buyers (per month) depending on the level of subsidisation

The findings suggest the decisive role of state support in stimulating EV adoption. This support takes different forms across countries, varying from direct subsidies upon purchase to indirect measures, such as free parking. The development of a network of ultrafast charging stations is also of key importance since charging stations are a complementary product for an electric vehicle [34—36]. On the one hand, a developed network of state-financed charging stations helps to overcome the initial inertia and ensure the minimum number of electric vehicles necessary for further sustainable EV diffusion (critical mass). On the other hand, a certain minimum of electric vehicles is required to stimulate the formation of a charging station network. In the environment of actively developing electric transport, private companies (including EV manufacturers, large oil and gas companies, private gas and charging station network operators, and venture capital and private equity funds) participate in creating the charging infrastructure independently and without state support.

The above model allowed us to evaluate various scenarios for the charging infrastructure development in the exclave Kaliningrad region. The novelty of the approach lies in the fact that the model can be adapted to any region with low levels of EV adoption and charging infrastructure development. Based on the modelling results, the following recommendations can be made.

1. Regions interested in a high EV adoption rate should promptly create the core charging infrastructure using their resources. As experiments have shown, this is especially important at the initial stage of launching the positive feedback loop 'the number of charging stations — the number of electric vehicles'. Creation of the minimum (critical) infrastructure sets market forces in motion, encouraging private participation in building of further EV infrastructure.

2. To launch the incentive program aimed at increase of the charging infrastructure usage, it is recommended to take measures aimed at ensuring the minimum EV fleet size in the region through public contracts or public-private partnerships with large companies.

In an environment with a poorly developed charging infrastructure, the introduction of a set of incentives stimulating the transfer from ICE cars to EVs is of key importance; this is especially true for direct subsidies paying for part of the purchase price for EVs. Our analysis shows that the amount of subsidies largely determines the rate of EV adoption. Regions willing to accelerate the transition to individual electric transport should develop a subsidy mechanism and allocate the appropriate funds for the first two-three years of the programme.

Further development of the model may be associated with the following tasks:

— it is necessary to validate preference curves for the EV price and the infrastructure development level; further research, including sociological surveys, focus groups, accounting for the geodemographic characteristics, etc. can serve to validate the model dependencies;

— the model can be supplemented with simulation tools, including agent-based modelling (i.e., for a more detailed analysis of consumer choice by including more factors affecting the EV choice, for example, non-financial incentives, and individual behavioural effects), and the system of spatial optimisation of the network of charging stations (based on GIS and traffic flow data, as well as on the condition of distribution networks).

The model operates in a demonstration mode and presents a general approach to the problem under study. The advantage of the system dynamics model is that it can be constantly calibrated and adjusted based on empirical observations on system development.

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