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Exploratory policy analysis for electric vehicle adoption in European countries: A multi-agent-based modelling approach

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ABSTRACT

To reach climate neutrality goals, European countries need to reduce their transportation sector emissions. To this end, implementing effective incentive policies to accelerate electrical vehicle (EV) adoption plays a vital role. With this study, we highlight the important role of governments, showing that even with the provision of certain mild non-financial incentives, such as charging infrastructure development, EV adoption rates can be significantly increased. We develop a multi-agent model of EV adoption within European countries up to the year 2030. This integrated framework can capture the interplay between technical, financial, and social aspects of the EV adoption process. We find that an annual increase of only 10% in the charging infrastructure incentives over ten years can increase the average European EV adoption rate to 46%. We observe that countries that have both a low level of charging point density and a high population density would benefit more from the provision of charging infrastructure incentives. Countries with lower overall achieved EV shares, on the other hand, are found to be relatively insensitive to such provisions. We also characterize how a higher level of charging point density will lead to more rapid EV adoption.

1. Introduction

Governments around the world, motivated by specific targets for climate change mitigation, have set several goals to increase electric vehicle (EV) adoption. The European Commission has aimed at cutting greenhouse gas emissions by at least 55% by 2030, which sets Europe on a responsible path to becoming climate neutral by 2050. To this end, the transportation sector will be one of the focus areas, as more than 90% of energy needs of this sector in 2020 were supplied via petroleum products, making it one of the largest contributors to greenhouse gas (GHG) emissions (International Energy Agency, 2021). After the US, Europe has the highest road transport emissions of around 0.90 $GtCO_2$ in 2021 (BloombergNEF, 2021). Since 2014, the GHG emissions of the transportation sector has increased every year, estimated to be 29% higher in 2018 than in 1990 (European Environment Agency, 2020). In recent years, however, thanks to the increasing share of EVs, the transportation sector is experiencing the largest reduction in energy demand (International Energy Agency, 2021), as EVs are around three times more efficient than conventional internal combustion vehicles. In this regard, the adoption rate of EVs is expected to increase in recent years due to their contribution to global and local emissions reduction, and also because of the accelerating actions taken by governments (Broadbent et al., 2021a). Decreasing the EU's reliance on fossil fuels will require putting on roads at least 30 million zero-emission vehicles by 2030 (European Commission, 2020). At least 90 per cent drop in mobility emissions are needed to attain climate neutrality by 2050.

A lot hinges on how fast EVs will be adopted by motorists. This is not easy to predict due to complex interactions between stakeholders (such as EV adopters, non-adopters, policy makers, industries etc.) as well as the uncertainties in decision parameters.

Social interaction and behavioral factors are shown to be important drivers of EV adoption (Hu et al., 2020; Shafiei et al., 2012; Yang et al., 2019). The perceptions of motorists, determined by their values, attitudes and knowledge, could influence their willingness to purchase EVs (Haustein and Jensen, 2018; Wang et al., 2021). In particular, social interaction with EV adopters and the word-of-mouth effect is an important driver of EV adoption. Sahoo et al. (2022) conduct an online survey among potential EV users to determine the motives of Indian

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youths toward EVs. Their findings highlight the importance of the word-of-mouth effect in EV adoption. A key factor in the diffusion of battery electric vehicles (BEVs) is consumer behavior, including attitudes and perceptions towards technology, price, availability, and knowledge (Secinaro et al., 2022). Social and psychological factors, such as socio-demographic characteristics and subjective norms, also influence consumer behavior. BEVs are generally viewed in a positive light due to their environmental benefits, operating costs, and government policies, while negative views abound due to concerns regarding battery recycling, energy sources, and increased driving distances. To effectively diffuse BEVs, a multi-scale approach that considers technology as well as behavior is necessary (Carlucci et al., 2018; Tran et al., 2012).

Availability of public charging infrastructure will be a key factor to motivate EV adoption. in fact, the insufficiency of the charging infrastructure is identified to be one of the most significant barriers to EV adoption in many choice modelling studies (Candra, 2022; Fu et al., 2021; Harrison and Thiel, 2017; Kumar et al., 2021; Potoglou and Kanaroglou, 2007). Public charging infrastructure investments are often incentivized by governments. The effect of government policies on EV adoption has been studied in literature for many countries (Ayyadi and Maaroufi, 2018; Peng and Bai, 2023; Srivastava et al., 2022). Haustein et al. (2021) study surveys of EV and conventional car owners that were conducted in 2017, 2018, and 2019 to assess the impact of fast charging installments in Denmark and Sweden. The authors suggest that EV adoption can be increased by improving the charging infrastructure among other actions.

Another factor affecting the speed of EV adoption will be the relative energy (fuel) price; that is, the price of electricity compared to that of diesel. Münzel et al.'s (Münzel et al., 2019) econometric study show energy prices to influence EV adoption positively and significantly in European countries.

To have effective policies, it is required not only to understand the adoption mechanism to model its dynamics and intervention effects (Deuten et al., 2020), but also to consider the uncertainty arising due to technical issues, technology progress, consumer preferences, and social interactions (Liu and Lin, 2017).

Based on these observations, we argue that the EV adoption rate in a country depends on three main factors: (1) social interaction, (2) availability of charging infrastructure, (3) relative energy price. To the best of our knowledge, no study in literature has addressed the interplay between these three variables on the rate of EV adoption for a given country. There is a need to understand how the interaction between charging infrastructure incentive provision of a government and the EV adoption rate will affect the dynamics of the EV adoption process in countries with different characteristics.

With the current study, we aim to fill the gap in literature by developing a realistic EV adoption model that considers the interactions between the social interaction, charging infrastructure and energy price effects. We combine the effects of these three factors in a Bass-type diffusion model that predicts the EV adoption rate for a given country. This rate, in turn affects the government's charging infrastructure incentive decision. We construct a multi-agent-based (MAB) simulation model and compare the simulation results between scenarios with different levels of charging infrastructure incentive by governments. The MAB approach allows us to capture the complex interaction (feedback effects etc.) between the government, "potential EV adapter" and "EV adapter" agents as well as letting us model uncertainties in the form of probabilistic input variables. We develop customized policy recommendations for 23 European countries between 2022 and 2030 depending on their population density and existing charging point density.

The rest of this paper is organized as follows. Literature review is conducted in Section 2. Section 3 presents our modelling framework and methodology. Section 4 reports the results of our agent-based simulation. Section 5 presents discussions about the implications of our model. Section 6 provides a summary of our work and elaborates on the limitations of our work and potential extensions.

2. Literature review

This work is related mainly to the literature on the driving forces of EV adoption, the literature on adoption modelling approaches, and the literature on implemented EV incentive policies in different countries. We discuss each of these in what follows.

2.1. Driving forces of EV adoption

Governments may drive the transition to EVs by means of several levers, including policy incentives, cost deductions and more strict environmental targets (Li et al., 2019). EV adoption in a country would be accelerated through stronger collaboration among governmental actors, financial services and technical assistance (Barkenbus, 2020). To make European policy instruments more effective, a step-up in ambition must be accompanied by an assessment of the policy mechanisms (Carley et al., 2019; Prakash et al., 2018).

Across European countries, a large number of EV incentives have been available, from tax reduction to direct payments. These incentives can be classified into financial and non-financial (e.g., charging infrastructure) types (Canals Casals et al., 2016; Fang et al., 2020). Financial incentives address reducing the vehicle's ownership cost. They can be divided into two groups as one-time (e.g., rebate, tax reduction) and recurring incentives (e.g., waiver on fees). Despite these incentives, a multitude of political, technical, fiscal, as well as market obstacles (European Commission, 2020; Fluchs, 2020) stand in the way of EV adoption.

Government policies aimed at reducing transport emissions alone would not be enough to fight climate change; in free-market economies, citizens must also take action (Broadbent et al., 2021a). A fundamental change in behavior by individuals and enterprises must drive the process of adoption (European Commission, 2018). Some consumers are shown to choose various types of EVs based on non-financial motives instead of meticulously calculating their lifetime costs (Contestabile et al., 2020; Heffner et al., 2007; Turrentine and Kurani, 2007). Furthermore, there are differences among individual consumers' preferences and interactions with other consumers regarding EVs diffusion (Broadbent et al., 2021b; Cho and Blommestein, 2015).

Undoubtedly, making smart energy-related decisions under the influence of internal and external factors and complex network models in an uncertain environment is challenging from the stakeholders' perspective (Hu et al., 2020). As a result, there is a need for a modelling framework addressing this problem environment that can simultaneously consider the effect of stakeholders' (EV adopters, policy makers, automakers and fuel suppliers) interaction with each other at the micro-level, as well as the effects of macro-level influences such as the energy and vehicle markets. This is what we do with the current study.

2.2. Modelling approach of the adoption process

Numerous aspects of energy system modelling and planning in the transportation sector have been studied in the literature (Reuter et al., 2021). Energy models as valuable tools for dealing with these complicated and complex problems have been dominated by "top-down", "bottom-up", and "hybrid" approaches (Neshat et al., 2014).

Economists and government officials use the top-down approach to analyze the macroeconomic impacts of particular policies (Cho and Blommestein, 2015; Pagani et al., 2019; Prina et al., 2021). Models of this type show diverse perspectives on the future of EV diffusion at both national and international levels as a result of disciplinary and structural differences (Deuten et al., 2020; Ou et al., 2021). A key problem with top-down approaches is that they tend to focus on the attitudes of the central decision-makers and overlook other stakeholders.

A bottom-up analysis focuses on a detailed investigation of energy

Table 1
Overview of modelling studies on EV diffusion.

#	Author(s)	Year	Modelling Paradigm			Time Horizon			Purpose			Model Type			Resolution Techniques
			Top-Down	Hybrid	Bottom-Up	Short-term	Med.-term	Long-term	Predicting	Forecasting	Exploring	Descriptive	Hybrid	Normative	
1	Novizayanti, D. et al.	2021			1			1			1			1	ABM
2	Ou, S. et al.	2021	1			1			1				1		Discrete Choice Modelling, Scenario Planning (NEOCC Model)
3	Deuten, S. et al.	2020	1					1		1			1		System Dynamic Model (PTTMAM model)
4	Ramchandran, N. et al.	2020			1		1		1					1	Bass Diffusion Model (System Dynamic + ABM)
5	Hu, Y. et al.	2020	1			1		1	1			1			NW Small-World Network, Evolutionary Game Theory
6	Fluchs, S.	2020	1					1	1					1	Technology Diffusion Model
7	Adepetu, A. et al.	2019		1		1			1					1	ABM
8	Pagani, M. et al.	2019			1			1		1	1			1	ABM
9	Zhuge C., and Shao C.	2019			1	1					1			1	Multinomial Logit (MNL) models and Moran's I
10	Qian, L. et al.	2019			1	1					1			1	Multinomial Logit (MNL) Models
11	Kangur, A. et al.	2017			1			1		1				1	ABM
12	Noori, M., and Tatari, O.	2016		1			1		1		1		1		ABM + Electric Vehicle Regional Market Penetration (EVReMP) Tool
13	Wolf, I. et al.	2015			1			1		1				1	Novel ABM, What-if Scenarios
14	Usher, J. et al.	2015		1				1		1			1	1	Diffusion Model
15	Cho, Y., and Blommestein, K.V.	2015			1		1				1			1	ABM
16	Shafie, E. et al.	2012			1			1		1				1	ABM
17	Eppstein, M.J. et al.	2011		1				1			1		1		ABM

technologies, such as the penetration of EVs and the necessary investments to support them (Connolly et al., 2010; Kangur et al., 2017; Novizayanti et al., 2021). Models following the bottom-up approach are usually formulated as optimization problems (Böhringer and Rutherford, 2008) that determine the most cost-effective technologies for satisfying a certain demand (Andersen et al., 2019), or as simulation models (Klinge Jacobsen, 1998). A detailed analysis of the elements and technologies found in the energy system is presented in (Gerossier et al., 2019); (Messner and Schrattenholzer, 2000; Murphy and Jaccard, 2011; Wolf et al., 2015). Bsisu, for example, recommends that the Jordanian government pursue the bottom-up approach to increase public understanding of green vehicles among different inhabitants, as well as to establish a socially acceptable price (Bsisu, 2019). Ramchandran et al. (2020) creates a model to predict how EVs would be adopted in India, and recognizes the essential bottom-up mechanisms affecting EV uptake. The authors use the Bass Diffusion Model to build a system-dynamics model and an agent-based model.

Agent Based Modelling (ABM) is a bottom-up method that aims to specify the macro behavior of a system by modelling individual agents and their interactions in simulation (Ding et al., 2018). ABM is useful in studying how system rules and patterns appear from agents' behavior (Watkins et al., 2009). With ABM, separate components of a system are described by discrete agents that operate independently within a simulated environment that can lead to non-intuitive results at the population level (Nejat and Damnjanovic, 2012). A bottom-up ABM approach is able to fill the gap between microscopic behavior and the macro aspects within a system (Ding et al., 2014). Methods such as ABM or systems dynamics have been used in most studies examining EV development, based on either top-down or bottom-up modelling approaches (Ramchandran et al., 2020; Shafiei et al., 2012; Usher et al., 2015).

The top-down and the bottom-up modelling approaches may generate contradictory policy prescriptions; in the literature, bottom-up models often propose policies to eradicate obstacles to reaching low-GHG technologies, while top-down models often recommend price-based policies such as taxes and tradeable permits to reduce GHG emissions (Jaccard et al., 2004). Unlike the top-down approach, which focuses on how well goals are met over time and why, the bottom-up approach inquiries about the goals, strategies, activities, and contacts of the individuals and groups within a system. The best way to avoid these either-or choices is to combine the best aspects of the two approaches (Sabatier, 1986). For instance, most researchers use macroeconomic models to assess climate change policy's economic influences. Nevertheless, such models fail to capture the exact physical properties of energy production and combustion technologies, and they often overestimate economic effects. A possible solution would be to connect top-down macroeconomic models with bottom-up energy sector models that can reflect technological elements (Timilsina et al., 2021) (Krook-Riekkola et al., 2017).

Combining the two modelling approaches will enable analyzing more complicated matters such as regulation of the transport sector and households, as well as energy tax policies that take into account the linkages between the energy system, the society, and the economy. Numerous studies have recently been carried out involving the soft-linking of energy models specific to different countries. For example, using the Electric Vehicle Regional Market Penetration tool, Noori et al. (Noori and Tatari, 2016) address the intrinsic uncertainties and hybrid policies related to EVs. They assess the potential market share of EVs in the United States for 2030 based on the determined policies. Eppstein et al. (2011) investigate the interconnections among different hybrid policies on plug-in hybrid vehicle acceptance using a spatially detailed agent-based vehicle consumer choice model. Table 1 illustrates a short description of some studies in which top-down, bottom-up and hybrid modelling paradigms have been used. Most of the articles reviewed in Table 1 deal with forecasting EV adoption over a long-time period (Deuten et al., 2020; Wolf et al., 2015).

Several studies have addressed path of transition to electric mobility using parametric methods, such as system dynamics, in which there is no support for parameter uncertainty. Luo et al. (2022) determine an optimal subsidy for EV adoption using a dynamic game approach that includes the cross-side effects of EV adoption and charging infrastructure expansion. Rahman et al. (2021) develop a model based on agent-based simulation to compare EVs, plug-in hybrids, and gasoline vehicles comprehensively. Huang et al. (2022) develop an agent-based evolutionary game model that incorporates consumers' microscopic behavior into the dynamics of the diffusion of charging stations. Charging stations and EVs are simulated and their impact on the network topology is explored. Noori and Tatari (2016) identify the potential market share of EVs in the US by 2030 using the Electric Vehicle Regional Market Penetration tool that they developed. The authors also use exploratory modelling approaches to assess market share uncertainties. Our study tries to tackle this problem by considering the uncertainties arising from the complex interaction between EV adopters and policy makers, which is often neglected with the exception of some works in the literature such as that of Noori and Tatari (2016).

2.3. Implemented policies of EV adoption

Adoption of electric mobility is influenced by a wide range of policies and factors which has been studied for many countries using a variety of methods (Ayyadi and Maaroufi, 2018; Corradi et al., 2023; Debnath et al., 2021; Ledna et al., 2022; Neshat et al., 2018; Zheng et al., 2022). Liu and Lin (2017) analyze socioeconomic data from 28 countries to develop a prediction model for the adoption of EVs. Three independent variables were used to develop the model: per capita GDP, percentage of renewable energy consumption, and gasoline price. Held and Gerrits (2019) conduct a study of e-mobility policies in 15 European cities. The authors identify national policy initiatives that were successful in promoting EVs. Li et al. (2022) integrate vehicle attributes, policy attributes, and psychological characteristics to examine personal carbon trading, tradable driving credit mechanisms, and consumer preferences for different policy instruments for Chinese consumers.

Through an online survey, Peng and Bai (2023) demonstrate that city incentives may increase EV uptake but are not sufficient to achieve a full transition. Sæther (2022) conducts an analysis of electric mobility policies and charging infrastructure in Europe from 2009 to 2019. The implementation of charging infrastructure is found to be essential to the electrification of transportation systems. Martins et al. (2023) classify 27 EU Member States according to how they promote EV technology. The authors find that EV deployment is still heavily influenced by financial incentives, whereas the charging infrastructure plays an equally crucial role in making or breaking their deployment.

Governments can also use business models to deploy EVs since they provide a framework for sustainable and profitable market growth (Secinaro et al., 2020). Business models can address challenges such as high upfront costs, lack of charging infrastructure, and limited consumer acceptance, which are often cited as obstacles to the widespread adoption of EVs (Afentoulis et al., 2022; Huang and Qian, 2021). As well as attracting private investment and entrepreneurs, a sound business model can facilitate partnerships with other stakeholders for the rapid deployment of EVs (Bohnsack et al., 2014). As a result of leveraging business models, governments can develop policies and strategies that will support the growth of EV markets (Ziegler and Abdelkafi, 2022).

By using a system dynamics model and combining it with a policy analysis framework, Setiawan et al. (2022) consider the effectiveness of policies aimed at developing EV market share in Indonesia. Their results suggest that the government should reduce consumer taxes on EVs. In the case of lagging in EV technology advancement, the role of these incentives is found to be more considerable. McCoy and Lyons (2014) simulate the adoption of EVs among Irish households using an agent-based threshold model of innovation diffusion. A nationally representative and heterogeneous agent population is developed using detailed survey microdata. A number of geographic areas of interest are then used to calibrate the agent population. By using a latent class binary model, Lu et al. (2022) examine how substitutional incentive policies affect the adoption preference of EVs after the phase-out of purchase subsidies. Our study contributes to this literature by integrating a bottom-up ABM model to a top-down one to capture the interaction between the energy system, the society, and the economy as well as allowing us model uncertainties.

3. The modelling framework and methodology

This section explains the underlying methodology and the modelling framework of our study in details. Our model development comprises three main phases: (i) Descriptive representation of the drivers of EV market adoption; (ii) Development of the agent-based simulation model; and (iii) Establishment of a calibrated baseline (Business as Usual) scenario and a number of policy intervention scenarios. In what follows, we first explain these phases. Then we discuss our data sources and explain how we group European countries for our policy analysis.

3.1. The multi-agent based (MAB) framework

We have developed a multi-agent-based model to estimate the market penetration of EVs in a country based on the interactive behavior of two agent types: "the policy maker" and "adopters". The main focus of the model is on the interaction between the interacting decisions of the EV adopters and the policy maker. Other effects are considered as exogenous variables. Adopters' adoption decisions are based on financial (energy prices), non-financial and social factors. Adoption decisions in turn influence the policy makers' incentive policy decision.

The policy maker agent represents the government that determines the level of public incentives to support EV adoption. The other agent type, "potential adopter" is an individual who may consider adopting an EV but is not sufficiently motivated to do so. "Non-potential adopters", on the other hand, do not consider adopting an EV even if this is financially attractive. A certain percentage (potential rate coefficient, φ %) of a country's population (P) are assumed to be potential adopters. Both adopters and nonadopters are assumed to be members of an abstract network. In each period *t*, a potential adopter becomes an adopter by adopting an EV with probability $AdRate_t$ as shown in Fig. 1. Based on our discussion in Section 1, three significant factors affect $AdRate_t$ at period *t*:

- The word-of-mouth effect ($AdWOM_t$) arising from social interaction with adopters,
- The incentive effect (Inc_t) that arises from the incentive provision decision of the policy maker,
- The energy prices effect ($EneEff_t$) that is related to the relative price of electricity compared to price of diesel.

We have developed three modules, i.e., the WOM Module, the Incentive Module and the Energy Market Module for the simulation algorithm such that the behavioral, financial, technical, and social aspects of the model can be considered simultaneously. In what follows, we first describe each of the three modules in detail, and then explain how their results are combined to calculate the $AdRate_t$ value using a Bass-type diffusion model. Lastly, we introduce our overall simulation algorithm and scenarios.

3.1.1. The word-of-mouth (WOM) module

Social network structures are mainly used to define the patterns through which already-adopter agents interact with one another, mainly to calculate the word-of-mouth, imitation, and social influences over time. In order to simulate the interaction among such "connected agents", we use the *k*-means Clustering Algorithm (Liu et al., 2018). Cluster analysis is used as an unsupervised task of grouping a set of

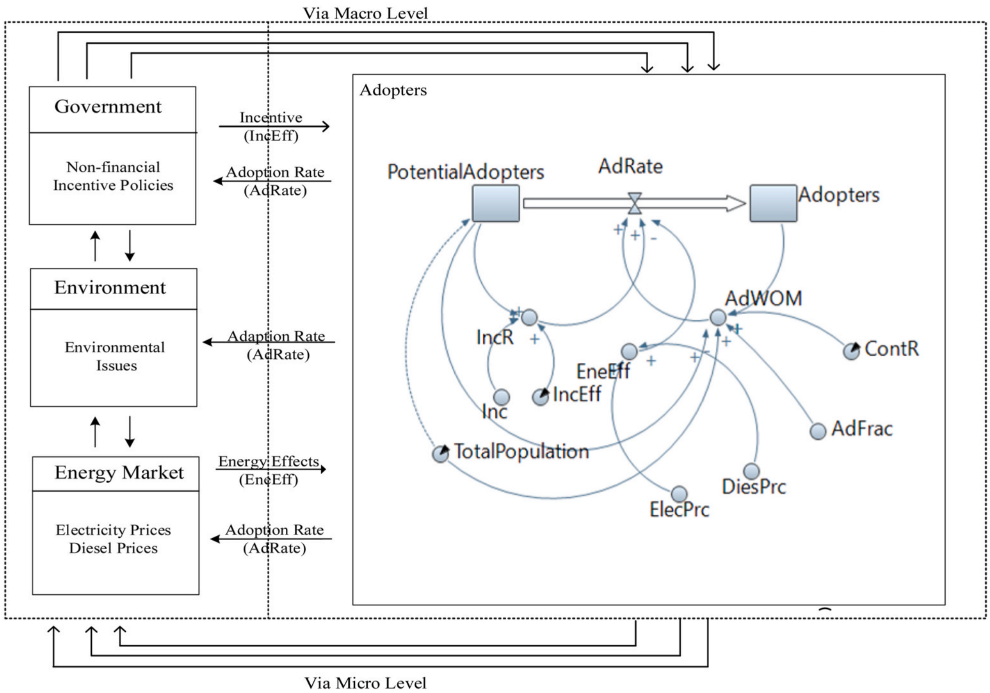

Fig. 1. The relations between the determinants of the EV adoption process.

agents such that the sum of distance squares is minimized within each group. The aim of the *k*-means algorithm in our model is to divide potential adopters within certain dimensions (which we do not model or explain explicitly) into *k* clusters where *k* denotes the number of adopters (α_{t-1}) at time *t-1*. The objective of the algorithm is to minimize the squared error which is:

$$MSE = \sum_{i=1}^{k} \sum_{x \in C_I} \|x - \mu_i\|^2 \tag{1}$$

where C_i, $\{i = 1,2, \ldots, k\}$ stand for clusters and μ_i is the mean vector of cluster C_i denoted as:

$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_I} x \tag{2}$$

In our model, each adopter agent contacts other agents (adopter or potential adopter) in its nearest neighborhood at the rate of $ContR_t$, forming a cluster of "connected agents" in the network. The potential adopters in this cluster are likely to adopt an EV based on the $AdFrac_t$ value. Accordingly, the "effect size" of WOM at time t, $\forall\, i$, $i = \{1,2, \ldots, \alpha_{t-1}\}$ is calculated as:

$$AdWOM_t = (ContR_t \times AdFrac_t \times \sum_{i=1}^{\alpha_{t-1}} \tau_t^i)/n_t \tag{3}$$

where $\tau_t^i = \text{Max}\, j$, and j is the index of connected agents to the adopter i in a cluster at time t. The term n_t represents the number of potential adopters.

3.1.2. The incentive module

In our model, the incentive is captured as the charging infrastructure support of the policy maker agent, i.e., the government. The variable Inc_t denotes the number of charging points at time t as the level of provided charging infrastructure. The value of the parameter $IncEff_t$, which captures the "effect size" of incentives is the related regression coefficient that is provided in Table 3.

Adopters' EV adoption decisions and policy makers' charging incentive provision decisions mutually affect each other. The autoregressive time series of Inc_t for the Business As Usual (BAU) scenario is considered as an exogenous variable and it is forecasted using the Anylogic software.

3.1.3. The energy market module

Energy carrier prices have a significant effect on transportation costs and hence, total cost of vehicle ownership. Based on our literature review, they have been found to significantly influence the past sales of alternative fuel vehicles. We formulate the effect size of energy prices ($EneEff_t$) as:

$$EneEff_t = \beta \log(ElecPrc_t \,/\, DiesPrc_t) \tag{4}$$

where $ElecPrc_t$ and $DiesPrc_t$ stand for the prices of electricity and diesel fuel at time t, respectively, and β_2 is the related regression coefficient that is provided in Table 3.

3.1.4. AdRate calculation

The $AdRate_t$ is calculated based on the three aforementioned modules. To model the diffusion of EV adoption as an infant technology, we chose to use the Bass Diffusion model, which is the most widespread used model for this purpose (Ayyadi and Maaroufi, 2018).[1] Accordingly, we calculate $AdRate_t$ for each time period t as:

$$AdRate_t = \left(\frac{1 - e^{-t(p+q)}}{1 + \left(\frac{p}{q}\right) e^{-t(p+q)}}\right). \tag{5}$$

The coefficient of innovation (p) in this standard Bass model is calculated based on the incentive effect and energy price effects of our model as follows

$$\log p = (IncEff_t \times Inc_t) + EneEff_t \tag{6}$$

The coefficient of imitation (q) in the standard Bass model, on the other

[1] It should be noted that the Bass model considers the growth of adoption rate as exponential, which reaches a peak and then again decays at an exponential rate. This makes it a suitable model for modelling the EVs adoption.

hand, is taken to be the WOM effect in our model.

$$q = AdWOM_t. \quad (7a)$$

Table 2 summarizes the parameters and the variables of our model along with their assumed statistical distributions.

3.1.5. The overall simulation algorithm and the scenarios

The consolidated version of the EV adoption algorithm that we implement in AnyLogic[2] Software is described in Fig. 2. Using this agent-based model, we simulate the following four separate scenarios:

- Baseline scenario (BAU): No more policy intervention (following the historical trend),
- Scenario-1: 10% increase in the number of installed charging points every year compared to BAU's increase,
- Scenario-2: 20% increase in the number of installed charging points every year compared to BAU's increase,
- Scenario-3: 30% increase in the number of installed charging points every year compared to BAU's increase.

These scenarios are designed to be optimistic and are hypothetical examples employed to understand the impact of increased infrastructure. We consider an annual time span. Each scenario is simulated 20 times, and the number of adopters is averaged across these 20 runs. At the beginning of each run, there is a warm-up period.

Each scenario corresponds to a round (r) of the simulation model in the flowchart of Fig. 2. We use a threshold value (ξ) to terminate the algorithm. A threshold value of zero is used to keep the value of Inc_t unchanged in the BAU scenario. For the other three scenarios, the threshold is assigned a large value to let the algorithm proceed to the subsequent scenarios. In this case, the value of Inc_t is increased as

$$Inc_t \leftarrow Inc_t \lambda \quad (7b)$$

where λ is a scenario-dependent parameter.

3.2. Model data and parameters calibration

We used the data from years 2014–2019 to develop the agent-based model, and used 2020 and 2021 data to test the model's projections. The effect size of the considered variables as given in Table 3 were taken from Münzel's findings (Münzel et al., 2019). This table displays the results of regression model coefficients for three variables while the effects of country-level are fixed.

Based on the values in Table 3, for example, keeping all other factors unchanged, a 1000 Euro higher financial incentive increases the EV adoption rate by about 5.4% (with 95% confidence) according to the country-fixed effects. The regression on disaggregated incentives assesses whether consumers react to the timing and kind of incentives differently. The estimated coefficient for overall financial incentives (0.054) is found to be less than that for non-financial incentives, that is, charging infrastructure (0.070). Interpreting the recurring incentive coefficient and effects may be misleading in some cases since the total savings generated relies on the vehicle holding time.

Table 4 lists the data sources on the variables and parameters of our model. The gasoline and diesel prices of four previous years (from 15 January) were taken from the statistical pocketbooks of 2017 and 2020 (European Commission, 2017, 2020). Because Iceland, Norway, Switzerland, and Turkey are non-EU-countries, their price data was gathered from the offices of the national statistics and the Word Banks's world development indicators (German Agency for International Cooperation). The data of taxes and fees for ownership and acquisition of motor vehicles in European countries were obtained from ACEA Tax Guides (European Automobile Manufacturers' Association).

Table 2
Overview of the parameters and variables of the model.

Variable Parameter	Description	Unit	Range or Reference
Inc_t	Number of charging points at time t	N	[0, 31120], St. D. = 3812
$IncEff_t$	The effect size of incentives (regression coefficient)	–	Table 3
$ElecPrc_t$	The price of electricity at time t	ct/kwh	[8.21, 33.87], St.D. = 4.9
$DiesPrc_t$	The price of diesel fuel at time t	Euro/l	[0.92, 1.80], St. D. = 0.18
$AdWOM_t$	The adoption rate of connected potential adopters at time t	–	Equation (3)
$ContR_t$	The probability of connecting to an adopter	–	Uniform (0, 0.03)
$AdFrac_t$	The adoption rate of potential agents that are connected to an adopter at time t	–	Uniform (0, 0.05)

3.3. Classification of countries

As shown in Table 5 and Fig. 3, we define nine potential country groups based on their population density and charging point density. Because no country falls into group 8, we have eight resulting country groups.

We use population density as a grouping characteristic as it influences the strength of social interaction among citizens. The population density affects the density of the abstract network of agents in our simulation model. As shown in Table 5, European countries vary considerably in population density (Worldometer). The charging point density, which is determined by the policy maker's infrastructure incentive provision, is chosen as the second grouping characteristic. This is because the effect size of charging infrastructure incentives (0.336) is found to be about 6 times larger than the one for one-time financial incentives (0.049) (Münzel et al., 2019). Thus, the size of the charging infrastructure may have significant feedback influences on the number of future adopters and hence, it is considered as the parameter of sensitivity analysis in this study. The European Alternative Fuels Observatory (EAFO) estimates 13 public charging points for each 100 km^2 for the whole of Europe in 2020 (i.e., for 32 countries, consisting of The United Kingdom and the EFTA countries Liechtenstein, Iceland, Switzerland, and Norway). Because the charging point density highly depends on country, we categorize the countries into low, medium and high charging point density as shown in Table 5. Germany has the average of 12 charging points for each 100 km^2. The Netherlands by the far has the highest value i.e., 130 points per 100 km^2, followed by Norway with 41 points per 100 km^2. Greece, Lithuania, Poland, Latvia, and Romania and Slovakia have the least number of charging points per 100 km^2 (Worldometer) .

4. Analysis and results

Here, we first compare our model's estimations with observed data from years 2020 and 2021. We then compare the results of the four scenarios. Next, we report sensitivity analysis results on the level of the policy maker's infrastructure incentive.

4.1. Comparison of model predictions with observed values

To validate the model, we analyze the results of one sample country from each of the 8 groups. As reported in Table 6, the absolute percentage error between our model's AdRate estimations and observed values in years 2020 and 2021 is less than 8%. Thus, the model performs

[2] https://www.anylogic.com/.

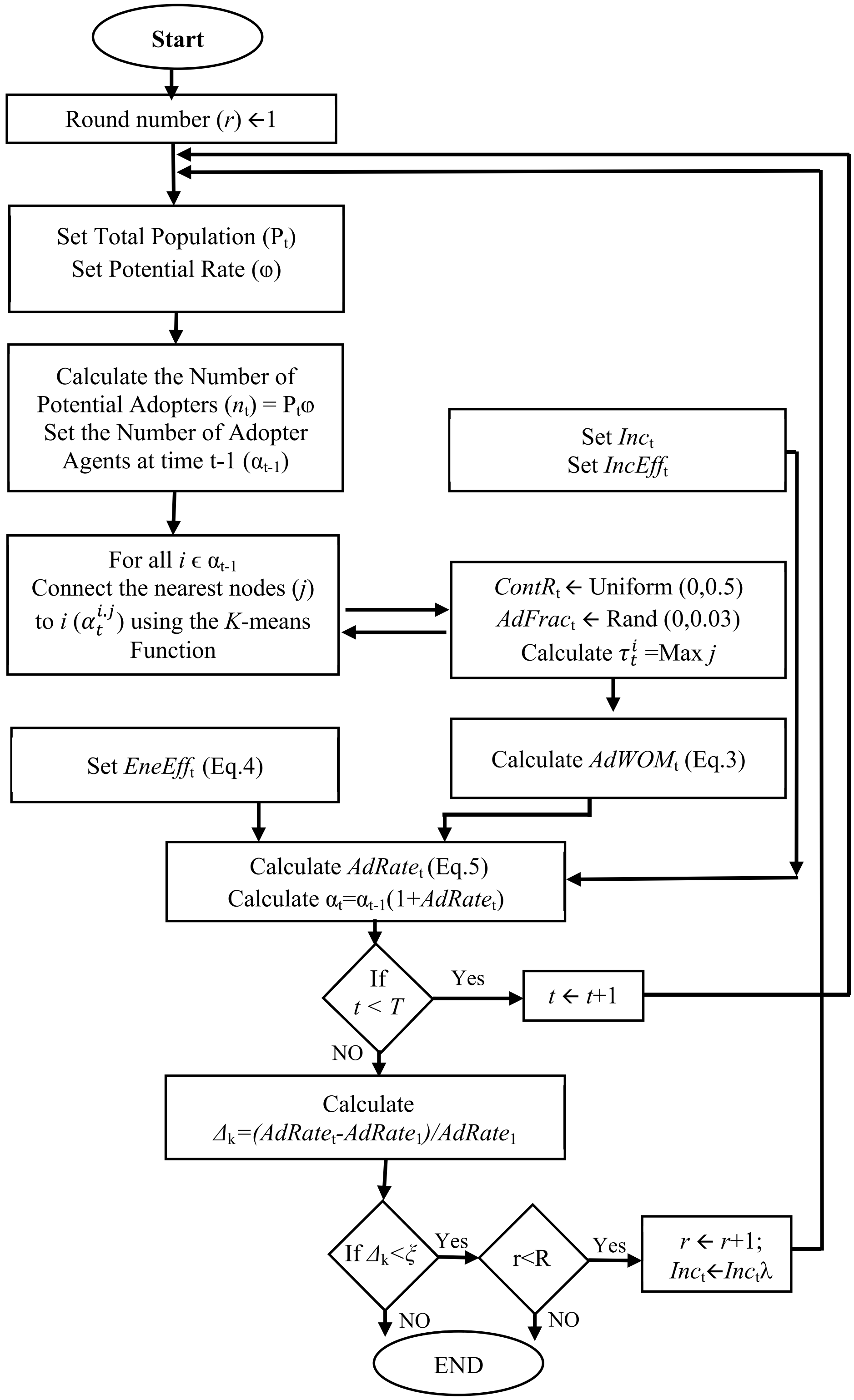

Fig. 2. The consolidated version of the EV adoption algorithm that was implemented in AnyLogic Software.

reasonably well. The observed values (real data) is gathered from ACEA Tax Guides (European Automobile Manufacturers' Association).

4.2. BAU scenario for comparison

After model validation, we have simulated the BAU scenario for each country to show the evolution of potential adopters' EV choice behavior without further policy intervention. Fig. 4 (the upper diagram), for example, depicts a section of adoption rate evolution for countries in group 7 which has high population density and low number of charging points. The points that are in the neighborhood of each other are connected by edges. If the state of an agent changes from potential adopter to adopter, it is marked with the orange color. Purple agents are those which are in contact with an adapter agent and have adapted through the WOM effect in the current period.

In the lower diagram in Fig. 4, the process of changing the state of

Table 3
Münzel's regression results related to EV adoption rate (Münzel et al., 2019).

Model	Aggregated Incentives (1)	Incentives by Recurrence (2)	Incentives by Type (3)
Financial incentives (1000 Euro)	0.054*		0.051*
	(0.031)		(0.021)
Non-financial incentives (1000 Euro)♣			0.070**
			(0.033)
One-time incentive (1000 Euro)		0.049	
		(0.031)	
Recurring incentive (1000 Euro)		0.336***	
		(0.087)	
Log (electricity price/ diesel price)	−0.196	−0.224	
	(0.569)	(0.576)	
Trend	2.224***	0.202***	
	(0.113)	(0.113)	
Observations	226	226	
Adjusted R^2	0.75	0.75	
F statistic	237.700***	180.161***	

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
♣ The coefficient is calculated only for charging infrastructure.

Table 4
Overview of sources.

Variable/Parameter	Source
$ContR_t$	Noori and Tatari (2016)
$AdFrac_t$	Linder (2011)
$DiesPrc_t$	EuroStat (2019)
$ElecPrc_t$	EuroStat (2021)
$IncEff_t$	Table 3
Inc_t	ACEA (2021)
Population Density[a]	EuroStat (2021)
ω[b]	EuroStat (2022)

[a] The average number of the people living in a specific area.
[b] The number of passengers' cars per inhabitant.

agents from potential adopters to adapters is depicted over time. After the warm-up period, this process proceeds based on the value of the adoption rate ($AdRate_t$). In this graph, the blue colored line shows the number of adapters at any time and the grey colored line shows the decreasing trend of the potential adapters over time.

Fig. 5 shows the increasing trend of the EV adoption rate from 2022 to 2030 for all country groups under the BAU scenario. The black dotted line shows the average trend over all European countries. We can see an *S*-shaped growth curve, in line with the diffusion curve of infant products introduced by Rogers (2003). On average, adoption rate in groups 1 and 7 (blue- and yellow-colored lines) increases from 1.33% and 2.04% respectively in 2022 to 8.97% and 14.72% in 2030. Passenger vehicle sales in the pioneering countries, Norway and the United Kingdom (orange and grey colored lines), are anticipated to be totally based on EVs by the end of 2025 and early 2026, respectively. The adoption rate in groups 4 and 2 (green and pink colored lines) will increase from 15.6% and 20.2% at the beginning of the time horizon to 36.14% and 45.7. Also, the increase of the adoption rate in groups 9 and 6, to 26.1% and 28.01% at the end of 2030 is evident.

4.3. Sensitivity analysis experiments

Here, we investigate the effect of increasing the number of charging points, that is the infrastructure incentive decision of the policy maker, on the evolution of EV adoption.

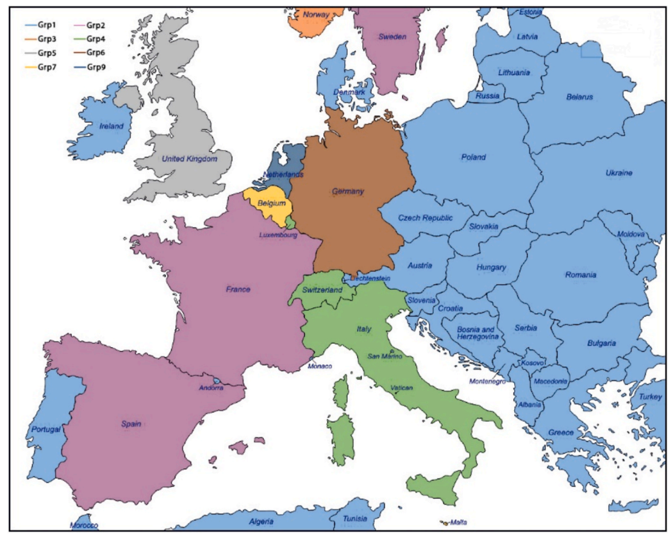

Fig. 3. Country groups.

Table 6
Comparing model predictions and observed values.

Country Group	Representative Country	Estimated $AdRate_t$/Real data (2020)	Estimated $AdRate_t$/Real data (2021)	Absolute % Error
Group 1	Finland	1.32/1.39	1.39/1.47	5.3
Group 2	France	20.29/21.55	21.31/22.59	6.1
Group 3	Norway	51.01/55.09	57.6/61.98	7.8
Group 4	Italy	15.75/16.54	16.25/17.03	4.9
Group 5	UK	32.10/34.83	34.77/36.05	3.6
Group 6	Germany	28.54/30.74	30.19/32.51	7.7
Group 7	Belgium	2.16/2.29	2.32/2.45	5.9
Group 9	Netherlands	26.03/28.03	28.20/30.26	7.5

Table 5
Country groups.

Group Number	Population Density (N/Km^2) Low (≤164)	Medium (165–375)	High (≥376)	Charging Point Density (N/100 Km^2) Low (≤40)	Medium (41–90)	High (≥91)	Countries
Group 1	✓			✓			The other European countries
Group 2	✓				✓		Sweden, France, Spain
Group 3	✓					✓	Norway
Group 4		✓		✓			Luxembourg, Italy, Switzerland
Group 5		✓			✓		The United Kingdom
Group 6		✓				✓	Germany
Group 7			✓	✓			Malta, Belgium
Group 8			✓		✓		–
Group 9			✓			✓	The Netherlands

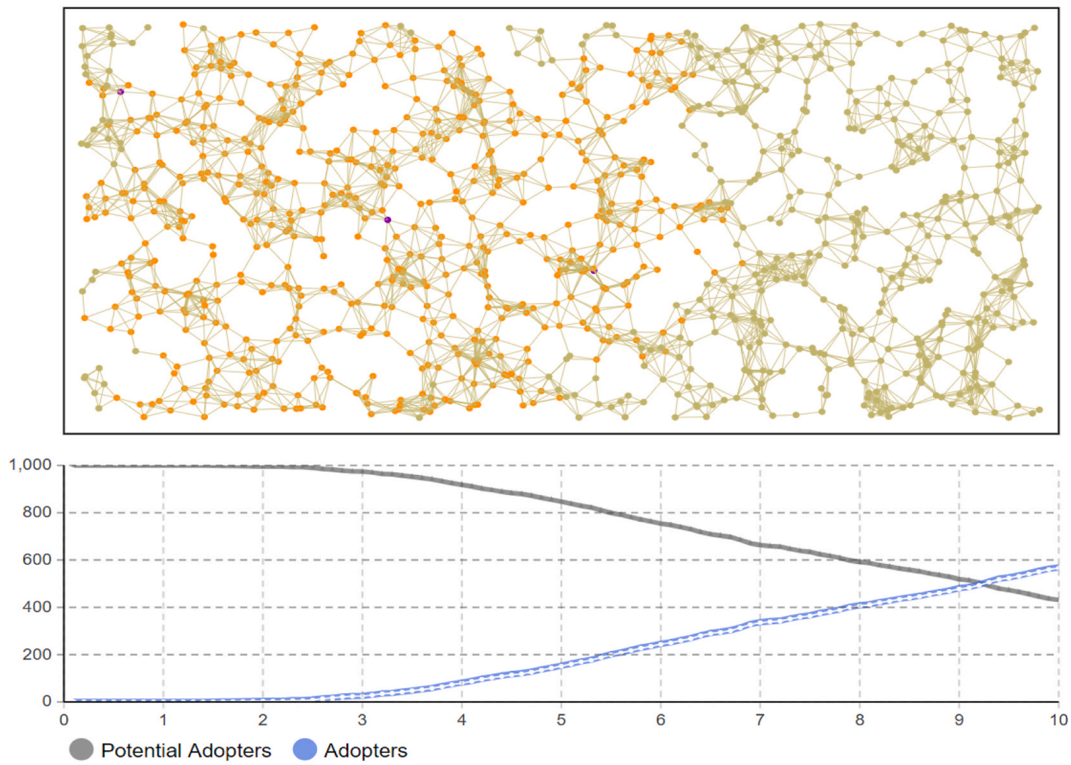

Fig. 4. The evolution of the EV adoption rate for group 7 under the BAU scenario.

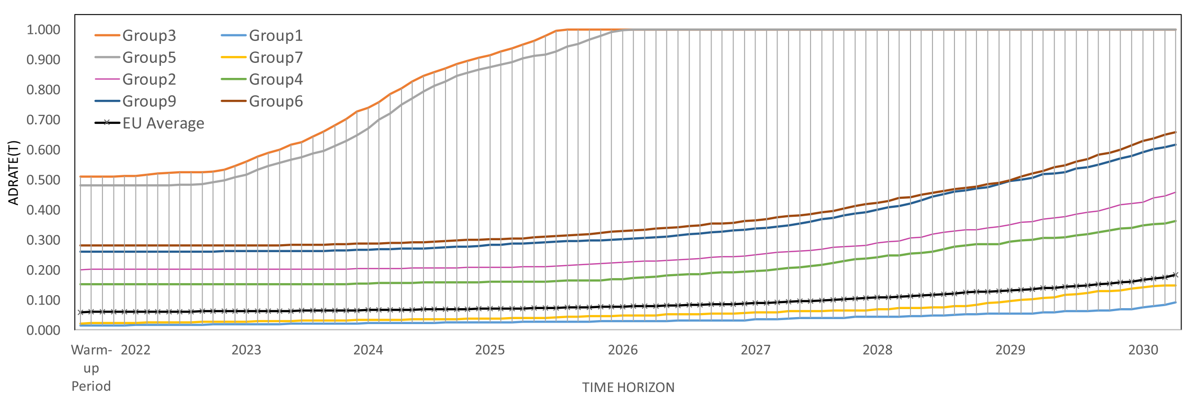

Fig. 5. The evolution of EV adoption rate for all country groups from 2022 to 2030 under the BAU scenario.

4.3.1. Policy intervention in low population density country groups

The results of implementing the incentive policies for group 1 countries, which are Finland, Hungary and Turkey, can be seen in Fig. 6. The evolution of adoption rate under the BAU scenario and scenarios 1, 2 and 3 are shown as blue, grange, grey and yellow lines, respectively. According to Fig. 6a, in these countries with low charging point density, EVs never achieve a significant market share by 2030. However, when the high level of incentives is in place, the impact of the intervention from 2022 to 2030 can be observed. Under the BAU scenario, the average adoption rate, which is less than 2% in 2021, is expected to increase to 8.9% by 2030. Under the further government intervention scenarios, however, this increase will accelerate and can even be tripled under scenario 3 which provides a 30% increase in the number of charging points per year. An annual increase of only 10% in the number of charging points over ten years can increase the growth rate of the adoption rate to 1.63 times more than that under the BAU scenario. If the number of charging points increases by 20%, this growth rate in the adoption rate will be 2.29 times more of that in 2030 on average.

In Sweden, France and Spain, which are included in group 2, the growth of the adoption rate under government intervention scenarios is lower than that of group 1 countries, but it is still noticeable. As can be seen in Fig. 6b, under scenarios BAU, 1, 2, and 3, the average adoption rate will reach 45.7%, 69.1%, 87.1%, and 95.9%, respectively.

Norway is the only country in group 3. Norway is a country with a low population density and a high charging point density. As shown in Fig. 6c, under the BAU scenario, only EVs will be sold in the Norwegian market by the beginning of 2026. This can be also achieved by early 2025 by implementing incentive policies to increase the number of charging points by 30% every year. Thus, the effect of policy intervention on the relative changes in the adoption rate will be lower compared to those of groups 1 and 2.

4.3.2. Policy intervention in high population density country groups

The countries of groups 7 and 9 are the those that have relatively

Fig. 6a, b, and 6c. Groups 1, 2, and 3 under different scenarios (from top to bottom, respectively).

high population density (more than 376 people per square kilometer). Fig. 7a shows that in group 7 consisting of Belgium and Malta, which have a low density of number of charging points, the adoption rate is less than 2.3% in 2021. Under the BAU scenario, the adoption rate will increase to 13.9% by 2030. However, under scenarios 1, 2, and 3, the average adoption rate would increase to 25.7%, 40.3% and 49.0% respectively.

Under the BAU scenario, the adoption rate in the Netherlands, a group-9 country, will increase from 26.2% to 59.1% by the end of 2030 (Fig. 7b). Under further government intervention, in Scenarios 1, 2 and 3, the growth rate can be increased by 30%, by 70% or doubled compared to the BAU scenario.

5. Discussion

In this section, we discuss the policy implications of our results. Under our BAU scenario, the average adoption rate for European countries, which is 5.8% in 2022, will only reach 18% by 2030. This projection is consistent with the results of Gnann et al. (2018). Figure 18% is far below the European Commission's goal of 55%, highlighting the need for European governments to increase their support for EV adoption. To this end, one effective policy is to bolster the incentives for increasing the number of charging points. Our results suggest that an annual increase of only 10% in the charging infrastructure incentives can increase the average European EV adoption rate to 46% by 2030, getting closer to the 55% target.

The European Commission recommends having one public recharging point per ten EVs, that is, 10 EVs per public charging point. However, there is a wide variation among the countries about this measure (Colmenar-Santos et al., 2019). Iceland and Norway have the highest ratio with 39 and 24 EVs per public recharging point. Ireland has 19 while the UK is closer to the recommended coverage with 13 EVs per charging point (McKibbin, 2021). Our findings may guide European countries in assessing the effect of their charging infrastructure incentives on EV adoption. In this regard, our results support the argument in literature (Gnann et al., 2018; Huang et al., 2021) that subsidizing charging facilities has a significantly positive effect on EV adoption.

We observe that countries that have both the lowest level of charging point density and the highest population density would benefit the most from the charging infrastructure incentives. On the other hand, countries with high overall achieved EV shares and high charging point density are found to be relatively insensitive to charging infrastructure incentives. That is, increasing the incentives for charging infrastructure may not always be the most effective means of promoting EV adoption. This finding is in agreement with the results of Fang et al. (2020). The case of countries that have both low achieved EV sales and low population density is also interesting. Due to their low starting values in the WOM effect, the EV adoption rates in these countries do not react

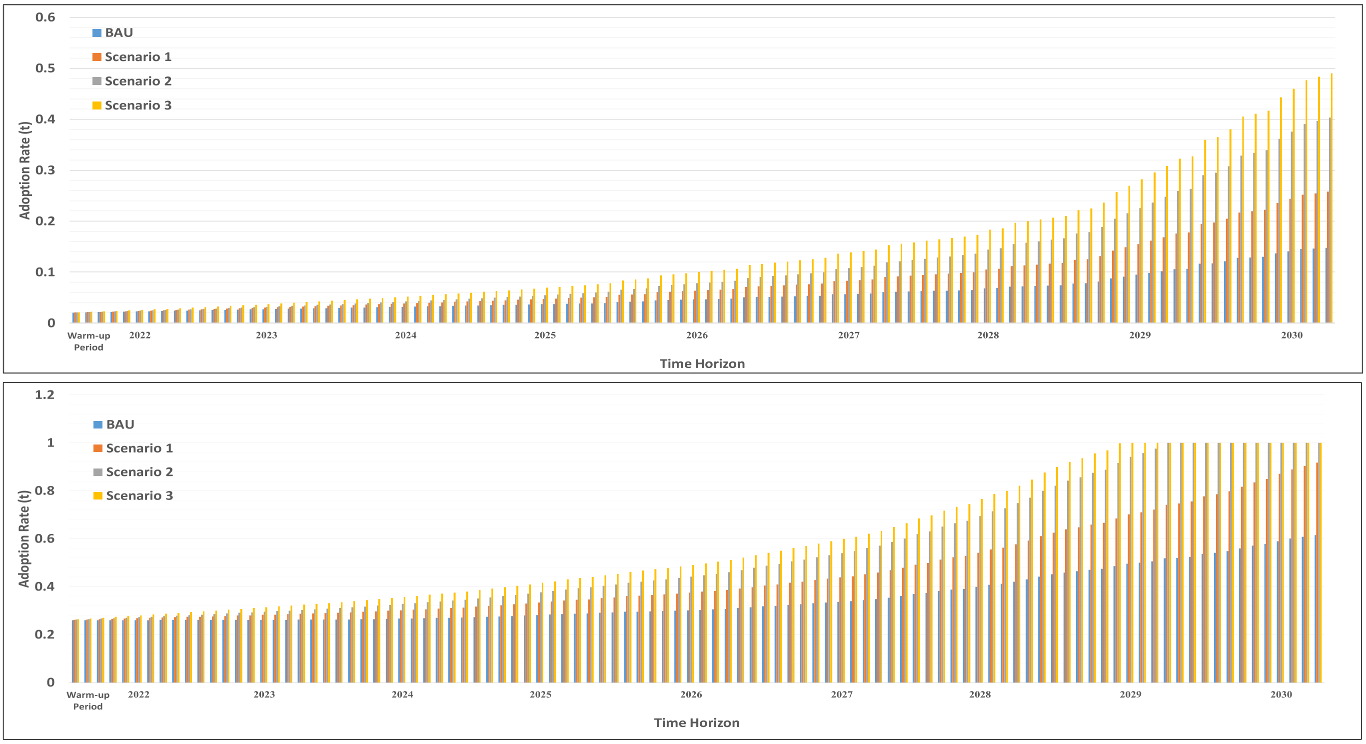

Fig. 7a and b. Groups 7 and 9 under different scenarios (upper and lower figures, respectively).

quickly to charging point provision.

6. Conclusion, limitations, and future works

In this paper, we developed a conceptual model of the EV adoption process in a country. The central construct in the model is the rate of EV adoption, which depends on three factors: (1) The word-of-mouth effect that arises from social interaction with adopters, (2) The charging infrastructure incentive that the government provides, (3) The relative prices of energy sources. We developed a multi-agent-based simulation model of the relationship where the actions of the policy maker and the adopters affect each other's choices. We used the simulation model to study the effect of charging point provision in different European country groups based on population density and existing charging point density.

Our contribution to literature is three-fold. First, we present a novel EV adopter decision logic that considers the interacting effects of social networks, charging infrastructure availability and relative energy prices. Existing studies only show that the number of public charging points positively affect the willingness to adopt EVs in European countries; however, the role of charging point availability in adopters' individual decision-making process and the underlying interactions have remained neglected. Second, by comparing four scenarios, we quantify the effect of the government's charging infrastructure incentive. Third, we came up with a number of policy recommendations as presented in Section 5, by studying different European country groups based on their population density and charging point density. According to the simulation and theoretical analysis results, some practical suggestions are drawn:

(1) Governments of countries with both low level of charging point density and high level of population density such as Belgium and Malta would benefit the most from the infrastructure provision incentives. These governments are suggested to focus on investment in charging infrastructure in their intervention portfolio. As we can see for Norway and UK, it is not surprising that a higher level of charging point density and market share of EVs lead to the most rapid and earliest EV adoption even under the BAU scenario, however, these countries are found to be relatively insensitive to charging infrastructure incentives.

(2) For group 1 countries, such as Hungary, Serbia and Turkey that have the lowest overall achieved EV shares and population density, we conclude that they are relatively less sensitive to charging point provision compared to Switzerland, Luxembourg and Italy that have medium EV shares and population density. This resembles a "Chicken and Egg" type vicious cycle. The governments of these countries are recommended to focus on other incentive policies such as developing awareness programs about environmental benefits of EVs, imposing high taxes on ICE vehicles as is the case in the Netherlands, Norway and Denmark, and providing attractive subsidies to bring the purchase cost of EVs in line with ICE alternatives as being done in France and Germany.

(3) It should be noted that although some countries such as the UK have not low density, there is geographically an uneven distribution of charging points within them. Given the importance of infrastructure provision, these governments not only need to provide charging point infrastructure but also are highly recommended to notice charging point distribution. Our model is detailed but remains a simplified representation of the decision processes of potential adopters and policy makers in the real world. For example, we use the overall "charging point density" as a measure; however, the distribution of these charging points in a country, that is, whether the charging points are concentrated on where they are needed, would also be important. To make the model more realistic, one can consider including "charging companies" as active agents in the model. Charging companies' price decisions would be an important determinant of the rate of EV adoption. In such a model, the government may need to decide how to allocate its budget between providing incentives to end consumers (adapters) and to charging companies. For example, Huang et al. (2021), find that a mix of policies including charging facility provision and government subsidies is the most effective strategy, where charging facility provision

accelerates the electrification of vehicles in the market and subsidies lead to consumption stabilization. Another extension is to consider a potential EV adopter population that is heterogeneous in its environmental sensitivity. In addition, our flexible simulation framework can be employed to address further policy questions such as the effects of changes in relative energy prices, and one can conduct simulation studies with different models of uncertainty (i.e., the input parameter distributions).

Despite all developments in the EV front, most motorists still have a perceived bias against a non-fossil fuel-powered vehicle (Huang et al., 2021). To overcome this, in addition to providing incentives, governments and enterprises may consider guiding consumers' awareness of EVs and pay more attention to the word-of-mouth effect. As a future work, it is highly recommended to develop an integrated assessment model to link the proposed module to an emission module in order to assess different transition pathway and carbon capture policies. Studies such as ours can provide guidance for such endeavors.

CRediT authorship contribution statement

Najmeh Neshat: Conceptualization, Methodology, Software. **Murat Kaya:** Data curation, Writing – original draft. **Sara Ghablulian Zare:** Literature review, Gathering data, Referencing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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