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Research Paper

Modeling Electric Vehicle Replacement with Discrete-time Markov Chains

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Abstract. As of January 2020, there are approximately 205,000 Electric vehicles and Plug-In Hybrid vehicles registered in The Netherlands. Most of these are leased vehicles. Electric Mobility has been rising in popularity in recent years, despite well-known limiting factors such as cost and performance. This makes it interesting to know how electric drivers tend to replace their vehicles. As in, with what probability do they transition back to an electric vehicle or alternatively, transition towards a different vehicle type? Transitions like these can usually be modelled with Markov Chains. This paper proposes a discrete-time Markov Chain model based on data snapshots of vehicle registrations from the RDW. The transition probabilities are based on the differences found between snapshots. For certain vehicle types, these tend to fluctuate over time, making it difficult to make long-term predictions. The number of registered electric vehicles in particular, are prone to outside stimulants such as government incentives.

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1 Introduction

In recent years electric mobility has become an increasingly popular way of transportation in The Netherlands. Businesses and government agencies are working together to stimulate the adoption of electric transport for its economic and environmental opportunities. Municipalities are stimulating e-mobility in order to reduce the amount of air pollution in the city by providing extensive public charge infrastructures and the Dutch government is also issuing subsidies on the purchase and leasing of electric cars [4].

The research program, *Urban Technology*, is part of the technical faculty at the Amsterdam University of Applied Science. Their focus lies on the development and application of sustainable technologies in order to create livable, sustainable and economically strong cities. One of their fields of research that follows this, is also electric mobility. As of January 2020, there are approximately 205,000 Electric Vehicles(EVs) and Plug-In Hybrid Vehicles(PHEVs) registered in The Netherlands[3]. This is about 2.3% of the total fleet of personal vehicles in The Netherlands. Since most of these electric vehicles are leased [2], Urban Technology is curious to know how *EV* and *PHEV* drivers replace their vehicles when, for example, their lease is up. Hence, the research question that we will answer in this paper is, with what probability will electric vehicle drivers transition to a specific vehicle type?

In order to gain insight into the replacement behaviour of electric vehicle drivers, data was acquired from the RDW containing information on all registered vehicles in The Netherlands, including the zip code in which the vehicle is registered. Unfortunately, by using this data it is impossible to determine which vehicles are leased or which belong to the same person. Instead, we will focus on how we can determine replacement behaviour by looking at the changes in vehicle registrations on a zip code level. We will do this by modeling the number of different vehicle types registered in The Netherlands as a *discrete-time Markov chain*. This will also enable us to make predictions of the future structure of the fleet of registered vehicles in the Netherlands and if the system is converging towards a steady-state given the current trends.

Chapter 2 discusses the related literature on the subject. Chapter 3 outlines the basics of Markov Chains that are used in this paper. In Chapter 4 we describe the data that was used from the RDW and Chapter 5 explains how Markov chains can be applied and how the transition probabilities can be estimated. Finally, the results are shown in Chapter 6 and conclusions are discussed in Chapter 7.

2 Literature Review

In this paper we will consider the "simple" Markov model, where a dynamic system has a given probabilistic law of motion [9]. These can be categorized into two models, namely the discrete-time Markov Chain and the continuous-time Markov Chain. With discrete-time Markov chains, state transition occur at fixed times, whereas with continuous-time Markov Chains, the time between state transitions is exponentially distributed. An introduction to Markov Chains is given in the books (Tijms, 2003), (Winston, 2003) and (Koole, 2014). Examples where Markov chains are applied within the context of population distributions are explained in (Lay, 2015) and (Fraleigh, 1995). Both show how Markov chains can be used to model population changes, make predictions and calculate steady-state vectors. (Winston, 2003) mentions similar examples but frames this as "*Work-Force Planning Models*". These also incorporate entries and exists of groups from outside the system.

Models that describe the interactions and dynamics of different populations are also often called *Markov Population Processes* or *Markov Population Models*. These have important applications in fields such as epidemics and biochemistry [6]. In these cases it is assumed that the Markov chain is continuous. Kingman (1969) gives a detailed account of the available methods to analyse these population processes.

3 Basics of Discrete-time Markov Chains

A stochastic process is a collection of random variables $(X_t,\ t \geq 0)$. A discrete-time Markov Chain is a special case of such a sequence of random variables where the state of the process changes at fixed, discrete times $t = 0, 1, 2, ...$ With continuous-time Markov Chains, the time between state transitions is not deterministic, but exponentially distributed. In the Markov Chain model, the future behaviour of the process only depends on the current state and not on its past history. Formally, the stochastic process $(X_t,\ t = 0, 1, ...)$ with state space I is called a discrete-time Markov chain if, for each $t = 0, 1, 2, ...$

$$P(X_{t+1} = i_{t+1} | X_0 = i_0, ..., X_t = i_t) = P(X_{t+1} = i_{t+1} | X_t = i_t) \tag{1}$$

for all possible values of $i_0, ..., i_{t+1} \in I$ [9]. This allows us to write

$$P(X_{t+1} = j | X_t = i) = p_{ij}, \tag{2}$$

where p_{ij} is the probability that the system will transition to state j at time $t+1$, given that it is in state i at time t. These are called *transition probabilities*. The transition probabilities are usually represented as a s x s matrix P, where

s is the number of states in the system:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1s} \\ p_{21} & p_{22} & \cdots & p_{2s} \\ \vdots & \vdots & & \vdots \\ p_{s1} & p_{s2} & \cdots & p_{ss} \end{bmatrix}$$

The *state-vector* x_t is a probability vector where the entries list the measurements of the system in each of the possible s states at time t. Together with the probability matrix P, the Markov chain can be described by

$$x_{t+1} = Px_t, \quad t = 0, 1, 2... \tag{3}$$

The *steady-state vector* π describes the long-run behaviour of the chain. When the system reaches this state after a large number of periods have passed, the population distribution will not change. The steady-state vector is the unique solution to the set of equations shown in (4), supplemented with $\pi_1 + ... + \pi_s = 1$. P is then the probability matrix for an *ergodic* Markov chain. A Markov chain is *ergodic* when all states in the chain are *recurrent*, *aperiodic* and *communicate* with each other [10].

$$P\pi = \pi \tag{4}$$

4 Data

In this section, we describe the vehicle registration data that was used for this research. First, we describe the different attributes of every registration and mention the timestamps of when a snapshot was taken of the database. Secondly, we explain which vehicle types can be attributed to a registration. Lastly, we show some basic information on how the number of different vehicle types evolves over time.

4.1 Vehicle Registrations

The RDW is an institute that registers all motorized vehicles and drivers' licenses in The Netherlands and has an extensive database at its disposal. Because the RDW does not store historical data, it is only possible to look at temporary snapshots of the database at various points in time. For this paper, 16 snapshots were available at different time points, ranging from November 2016 until January 2020. The time between snapshots varies from one to four months.

The snapshots contain all the vehicle registrations in The Netherlands along with identifying characteristics such as vehicle brand and model, date of first registration, fuel codes and emissions. The data consists of 36 attributes, but only a small number of these are used for this analysis. The used attributes are defined in Table 1. The snapshots contain around 10 million rows each or about 9 million unique vehicle registrations. EVs and PHEVs account for around 0.05% and 1% of the total number of registrations, respectively.

Attribute	Description
NUMMER	Hashed license number.
REG_DAT_AANSPR	Date from which the registered owner is liable for legal vehicle obligations and insurances.
POSTCODE_NUMERIEK	First 4 digits of the Zip Code where the vehicle is registered.
POSTCODE_ALFANUMERIEK	Last 2 letters of the Zip Code where the vehicle is registered. Only available for the G4 cities Amsterdam, Den Haag, Rotterdam and Utrecht
TYPE_BESCHR_VTG	Model description of the vehicle e.g. 'V60 PLUG IN HYBRID'.
MERK_BESCHR	Brand description of the vehcile e.g 'VOLVO'.
BRANDSTOFCODE	Fuel Code e.g. B = Gasoline, E = Electric, D = Diesel, W = Hydrogen.
VERBR_COMB	Combined fuel consumption in l/100km, during a combination city- and out of city trip. Tested on a dynamometer.
EMIS_CO2_COMB	Weighted emissions of CO2 in g/km of a plug-in hybrid vehicle during a combination city- and out of city trip. The value is calculated based on the emissions that occur when driving once with a empty battery and once with a full battery.
EM_CO2_COMB_TG	CO2 emissions of a vehicle, tested on a dynamometer. Applicable to electric hybrid vehicles that can recharge externally. (met een oplading van buitenaf gewogen gecombineerd volgens de berekening in de richtlijn.)

Table 1: Data attributes used

This analysis is limited to registrations that contain a zip code with an alpha numeric. These data are limited to the G4 cities Amsterdam, Utrecht, Rotterdam and The Hague. This means that only 9% of the total number of registrations will be used in this analysis, which equals around 0.03% and 0.1%, respectively, of the total number of EVs and PHEVs.

Table 2 shows that the time between snapshots is not evenly distributed. In order to even this out, 3 snapshots will not be used so to keep a time difference of around 3 months.

Snapshot	Date	Used
1	30-11-2016	
2	02-01-2017	✓
3	03-04-2017	✓
4	29-05-2017	
5	13-07-2017	✓
6	02-10-2017	✓
7	02-01-2018	✓
8	23-04-2018	✓
9	08-06-2018	
10	02-07-2018	✓
11	01-10-2018	✓
12	02-01-2019	✓
13	01-04-2019	✓
14	01-07-2019	✓
15	01-10-2019	✓
16	02-01-2020	✓

Table 2: Timestamp Data Snapshots

4.2 Vehicle Types

It is possible to attribute a vehicle type to a vehicle registrations. These types are derived from a flowchart from *The Rijksdienst voor Ondernemend Nederland* (RVO), shown in figure A.1. The RVO uses this flow chart to publish official monthly reports on the number of electric cars in The Netherlands. The flowchart is fairly straightforward and the flow is mainly determined by the vehicle's fuel codes, weight and certain carbon emissions. Using this flow chart, we can attribute the following vehicle types to a registration:

1. *ANDERS*: Vehicles without electric energy sources. This includes Diesel and Gasoline vehicles.
2. *ONBEKEND*: Vehicles that weigh more than 3.5 tons e.g. buses.
3. *EV*: Electric Vehicles.
4. *HEV*: Hybrid Vehicles.
5. *PHEV*: Plug-In Hybrid Vehicles.
6. *ANDERS HYBRIDE*: Energy sources include hydrogen.
7. *BRANDSTOFCELLHYBRIDE*: Hybrid with a fuel cell.

We will only consider the four main vehicle types namely *ANDERS*, *EV*, *PHEV* and *HEV*. This is because these make up the bulk of the observations. Figure 1 shows the total number of registrations over all snapshots. The first graph only shows a slight growth, of around 0.002% on average, in total fleet size. Especially around July 2018 and July 2019. The bottom two graphs show the percentages of vehicle types in the fleet. These show a small decline in the number of vehicles of type *ANDERS* and *PHEV* while the *EV*s and *HEV*s are rising.

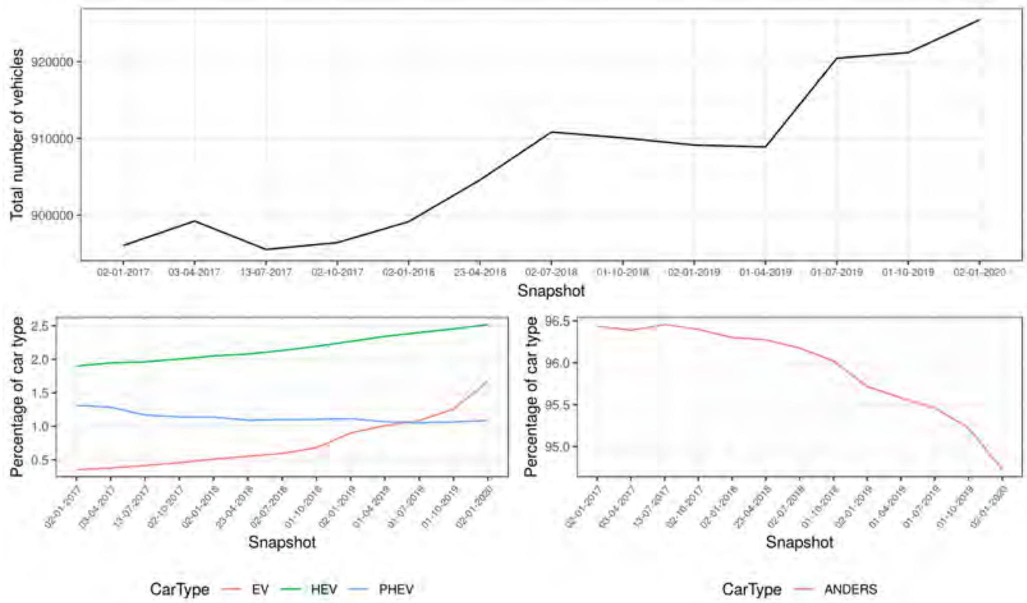

Fig. 1: Total number of vehicles VS corresponding proportions of vehicle types

When comparing 2 consecutive snapshots, the difference between them shows which registrations are new to the system and which registrations have disappeared from the system. Figure 2 shows the difference between the number of new registrations and the number of disappeared registrations when comparing consecutive snapshots.

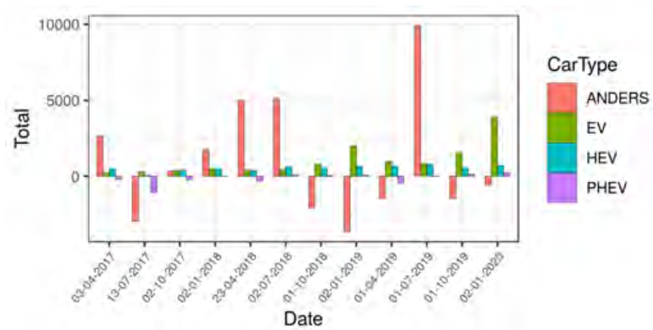

Fig. 2: Total number of new registrations minus the number of disappeared registrations

Type *ANDERS* again shows peaks around July 2018 and July 2019 meaning that there are much more new registrations than registrations that disappear from . This type also alternates between positive and negative values and seems to show the same wave pattern every year. However, type *EV* and *HEV* show positive values. Meaning that these types always increase in the number of new registrations. Especially the number of *EVs* is growing rapidly when compared to *PHEV* and *HEV*. Type *PHEV* shows values around 0, meaning that the number of *PHEVs* that disappear from the system is around the same number of new registrations of *PHEVs* that enter the system.

5 Methodology

In this section, we first discuss how the number of registered vehicles is modeled as a discrete-time Markov model. Secondly, we explain how the transition probabilities are estimated.

5.1 Discrete-time Markov Model

The total population of registered vehicles in a snapshot can be described as a vector with 4 elements, each element containing the proportion of a vehicle type. In our case the types *EV*, *PHEV*, *HEV* and *ANDERS*. For example, the population in snapshot 2 would result in the vector $[0.0036, 0.0132, 0.0189, 0.9643]$. This would mean that 0.36% of registered vehicles are *EV* and 1.32%, 1.89% and 96.43% are, respectively, *PHEV*, *HEV* and *ANDERS*. When taking a step from one snapshot to another, each of these vehicle types can transition to other vehicle types with a certain probability. For consistency, we will denote the time t with the snapshot numbers.

Now, define for $t \,\epsilon\, \{2, 3, 5, 6, 7, 8, 10, 11, 12, 13, 14, 15, 16\}$ the random variable X_t as

$$X_t = \text{a vector containing the proportion of vehicle types at time } t \tag{5}$$

Then X_t is a discrete-time Markov Chain with state space

$$S = \{[y_1, y_2, y_3, y_4] \,|\, y_i \,\epsilon\, [0, 1], \sum_i y_i = 1\}$$

The transition matrix P contains the transition probabilities between vehicle types. Accordingly, the entries p_{ij} are equal to the probability that an individual will replace a vehicle type i with vehicle type j, one snapshot later.

$$\mathrm{P} = \begin{array}{r} \\ EV \\ PHEV \\ HEV \\ ANDERS \end{array} \begin{array}{c} \begin{array}{cccc} EV & PHEV & HEV & ANDERS \end{array} \\ \begin{pmatrix} p_{11} & p_{21} & p_{31} & p_{41} \\ p_{12} & p_{22} & p_{32} & p_{42} \\ p_{13} & p_{23} & p_{33} & p_{43} \\ p_{14} & p_{24} & p_{34} & p_{44} \end{pmatrix} \end{array}$$

5.2 Estimating Transition Probabilities

The mutations between consecutive snapshots show the appearance of new vehicles and the disappearances of existing vehicles in the data. For example, by comparing snapshot 1 and 2 we can see which vehicles from snapshot 1 are no longer in snapshot 2 and which are new in 2 because they were not present in 1. By considering these mutations, it is possible to see the change in the population of vehicle registrations in a zip code. In order to try and distinguish individual vehicle replacement/transition in a population, we will limit ourselves to zip codes with an alpha numeric since this is a smallest area possible in the data to distinguish the possible behaviour of individuals.

Now consider only those zip codes with the same number of mutations. In these cases, an equal number of vehicles have disappeared as well as appeared from one snapshot to another. When the number of disappearances in a zip code are all of one vehicle type, we can see which vehicle type has appeared in its place. The same can be said for the case when the number of appearances are all of one vehicle type. These cases will be called *vehicle replacements* or *vehicle transitions*.

Figure 3 shows examples of the different scenarios that can occur between snapshots on a zip code level. The scenarios being multiple and single transitions.

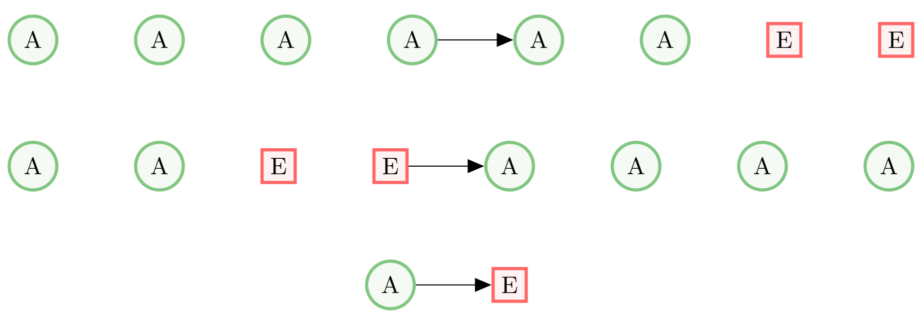

Fig. 3: Possible vehicle replacement scenarios within 1 zip code with vehicle type ANDERS and EV

The first scenario shows multiple transitions where four mutations take place in a zip code. This means that four vehicles of type *ANDERS* have disappeared and two vehicles of type ANDERS and two of type *EV* have appeared in their place. So in this zip code, type *ANDERS* experienced a 50% transition to type *EV* and a 50% transition to type *ANDERS*. In the second scenario, again with four mutations, two type *ANDERS* and two type *EV* transition into four type *ANDERS*. In this case, both type *EV* and type *ANDERS* show a transition of 100% to type *ANDERS*. The final scenario shows a single transition where 100% of type *ANDERS* transitions into type *EV*.

The probabilities based on these changes over all zip codes that meet the criteria for *vehicle replacements*, will form the estimates for the transition probabilities.

In the data there are a few exceptions that stand out. For example, vehicles that have moved with their owners will appear as a replacement due to the changed zip code. However, these should not be considered as a possible replacement and are hence removed from the results. They are distinguishable by a change in zip code, but not in liability date. Also lease companies tend to have a high number of vehicle registrations in a zip code since these vehicles are either registered at the lease company or at the company that leased them. These fleets will be treated as containing replacement behaviour with the above mentioned cased.

6 Results

This section discusses the obtained results. Section 6.1 describes the transition probabilities that are based on the single transitions over all snapshots. This section also shows which vehicle brands *EV* and *PHEV* users choose as replacement. Section 6.2 discusses the transition probabilities based on all single and multiple transitions with the same number of mutations. These probabilities are shown for every two consecutive snapshots. Section 6.3 discusses the prediction results for the different cases of transition probabilities mentioned in the previous section. Finally, Section 6.4 goes into the steady-state vectors that result from using the transition probabilities that produced the best prediction results.

6.1 Single Transitions

When only considering the single transitions, we end up with a total of around 77500 observations across all snapshots with about 6300 observations per transition. However, 94% of these observations are vehicles of type *ANDERS* being replaced by the same type. Figure 4 shows that for most replacements, the change is made to type *ANDERS*. Of the 141 *EV* cases 50% replace their vehicle with another *EV*. Respectively, 45%, 4% and 1% replace with type *ANDERS*, *PHEV* and *HEV*. For the 379 *PHEV* cases, 16% replaces with another *PHEV* while 18% goes for type *EV*. Type *ANDERS* makes up the bulk of the results with 76089 observations followed by 911 *HEV* cases.

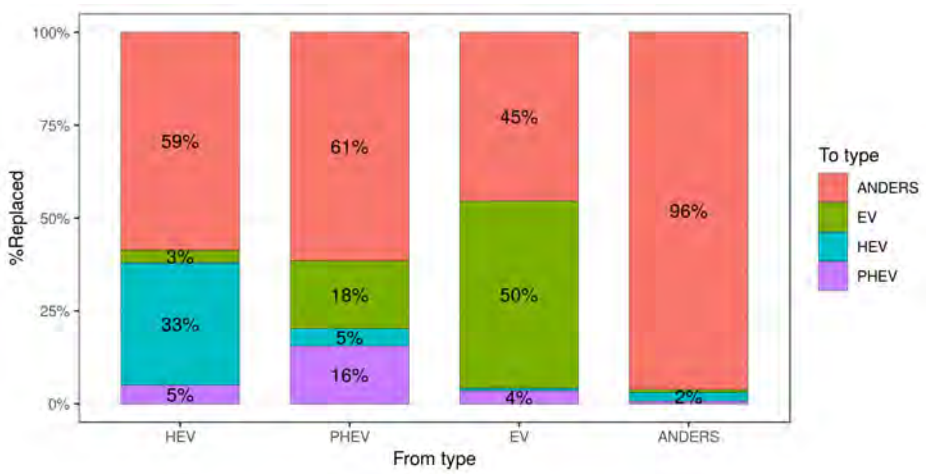

Fig. 4: Transition probabilities based on total number of single transitions

Figure 5 shows which vehicle brands *EV* and *PHEV* users choose as replacement. The x-axis showing their current vehicle brand and the y-axis showing the brand to which they transition. The most notable point shows that most Tesla users seem to replace their vehicle with another Tesla. Also *PHEV* Mitsubishi users, in this case the Mitsubishi Outlander series, show scattered replacement behaviour along a number of brands, but mostly still show preference for both Tesla and Mitsubishi as replacing brand. Volvo users also seem to prefer their own brand as replacement. And while most of these observations replace with a vehicle of type *ANDERS*, the upper half of the plot, with the cases where the move is made to an *EV* or *PHEV*, shows a somewhat linear trend. This would suggest that when an *EV* or *PHEV* user makes a transition back to a *EV* or *PHEV*, they tend to choose the same vehicle brand.

The replacement behaviour where users replace with an *EV* or *PHEV* is shown in Figure 6. Again, this graph shows Tesla as a popular choice as a replacement vehicle across multiple brands. Especially when considering BMW, Volkswagen, Volvo and Tesla itself.

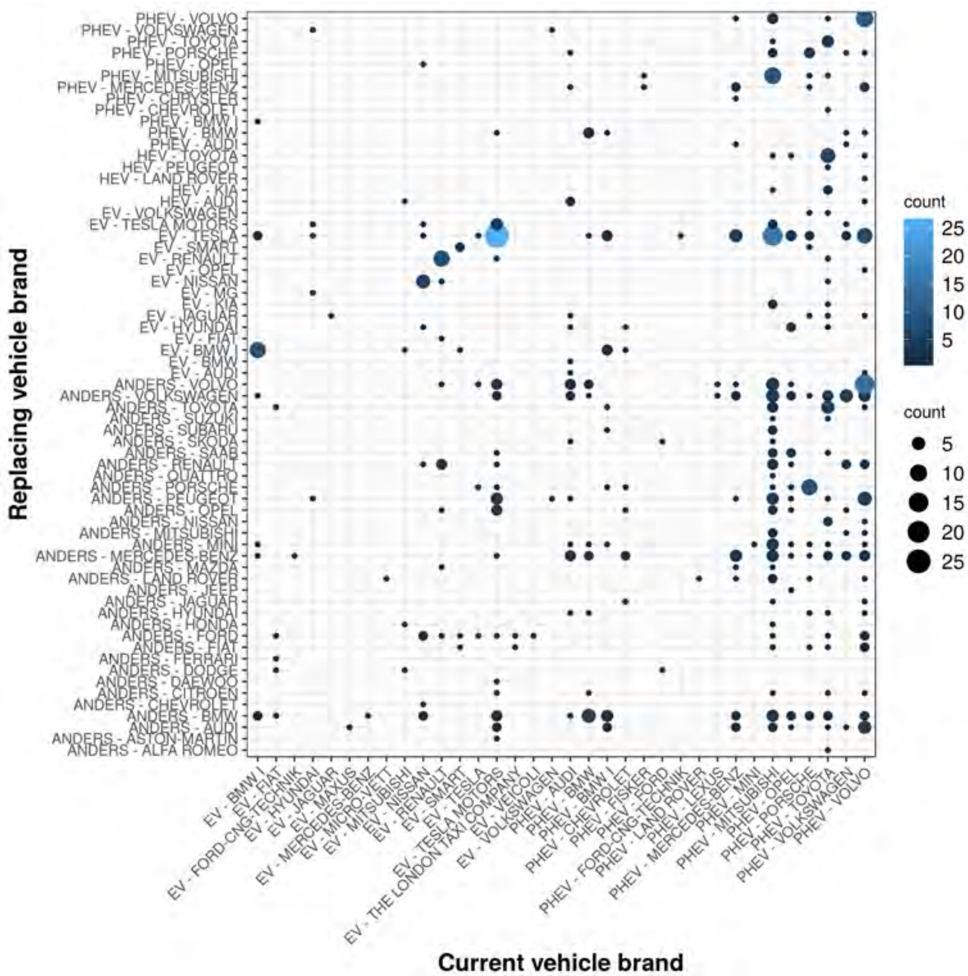

Fig. 5: Vehicle replacements for EV and PHEV drivers based on single transitions

6.2 All Transitions

When we consider all single transitions and all multiple transitions with the same number of mutations, we obtain a total of 178000 results over all snapshots with around 14000 results per snapshot transition. The resulting probabilities for every transition between two consecutive snapshots is shown in Figure 7. Every four transition charts corresponds to one year. The transitions 2-7 cover the period January 2017 to January 2018, 7-12 cover 2018 to 2019 and 12-16 cover 2019 to 2020. Ideally, these probabilities would be constant over time. However, Figure 7 shows that this is not the case. They show heavy fluctuations over time except for type *ANDERS*, which seems to stay stable with around 96% transitioning again into type *ANDERS*, 2% into *HEV* and about 1% going to *EV* and *PHEV* each. Although, the transitions made from *ANDERS* to *ANDERS* do seem to be dropping over time.

The transitions for type EV fluctuate the most especially in the beginning of the snapshots. For most transitions, EV users appear to transition to only type ANDERS and EV. The transitions $7-8$, which is around April 2018, shows a small percentage that also transitions to type $PHEV$ and HEV. This happens again in May 2019 with transitions $12-13$, where a small percentage transitions to $PHEV$. This keeps recurring since this time period. The fluctuating transition probabilities for type EV can also be attributed to the fact that these probabilities are, when compared to the other vehicle types, based on the least number of observations (see figure A.2).

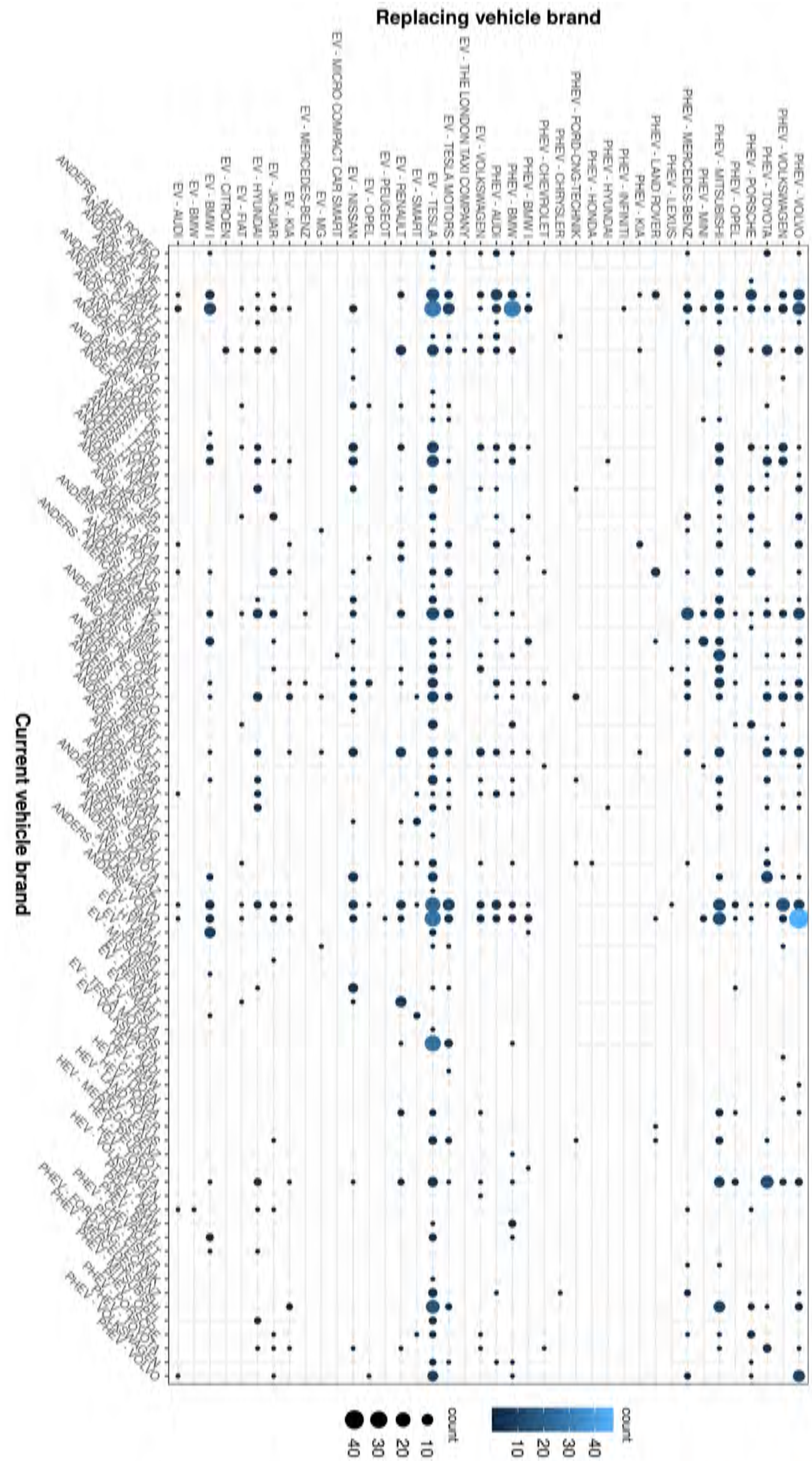

Fig. 6: One on one vehicle replacements for EV and PHEV drivers based on 415 observations

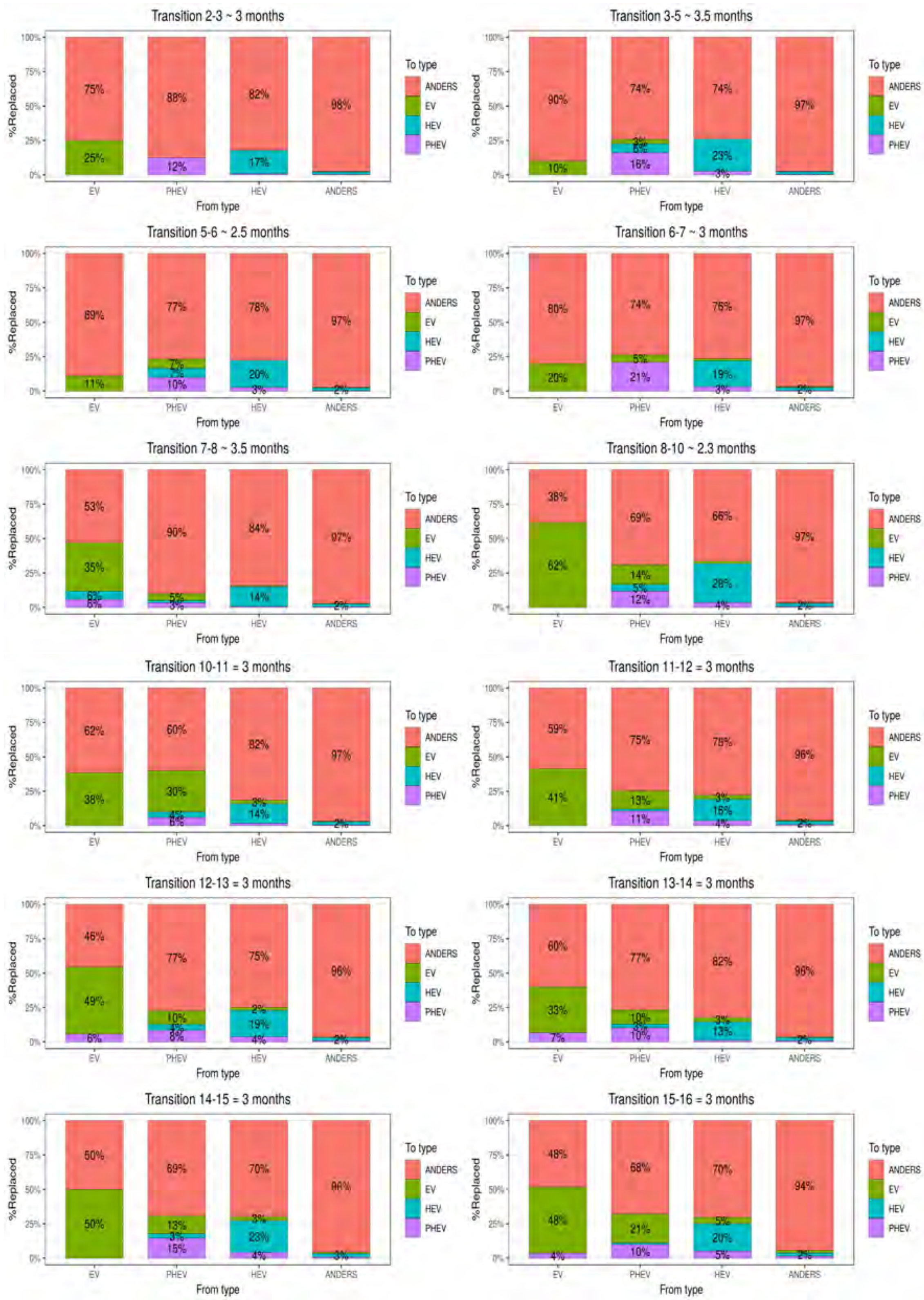

Fig. 7: Transition probabilities based on single and multiple transitions

6.3 Predict

Given that the transition probabilities tend to fluctuate through time, we will use each transition matrix shown in Figure 7 to calculate the one-step ahead predictions, $\hat{X}_t$, of this chain. We can then evaluate a performance metric of these predictions to determine which transition matrix best suits the Markov Chain. For each snapshot state X_t, we will calculate the predicted next state, $\hat{X}_{t+1}$, for each transition matrix P_i as mentioned in Equation 6. This will result in 12 state predictions for every 12 transition matrices.

$$\hat{X}_{t+1} = P_i X_t, \quad t \,\epsilon\, \{2, 3, 5, 6, 7, 8, 10, 11, ..., 16\},\ i = 1, 2, ..., 12 \tag{6}$$

In order to evaluate these predictions, we will use the absolute error and relative error. These are calculated by the formulas given in (7) with y being the measured value and $\hat{y}$ the predicted value. The relative error was also added since the percentages of electric vehicle types tend to be small, which makes the absolute error unreliable. We will also have to keep in mind that the true value y will not take on the value 0 in this case.

$$abs.err. = |y - \hat{y}| \qquad rel.err. = \frac{|y - \hat{y}|}{y} \tag{7}$$

Figure 8 shows the results for type *EV* and *PHEV*. The errors for *EV* show a fickle pattern with a turning point in October 2018, where half of the transition probabilities cause a drop in the absolute error and the other half a rise.
October 2018 is also the time when the proportion of *EVs* started rising heavily. Before this time period a large portion of the absolute error falls between 0.2 and 0.6 which is high, considering the fact that the number of *EV* registrations only rises about 0.1% during this time. This is also evident in the high relative error. These high error results follow from the probabilities based on later snapshots when the proportion of *EVs* was significantly higher than before. This effect also manifests itself in the errors that start low and steadily rise as time passes since these follow from the transition probabilities based on earlier snapshots. This of course means that the performance of the transition probabilities is heavily influenced by the underlying trend of the proportion of *EVs* in the fleet of vehicle registrations.
For type *PHEV* there is a clear distinction in performance, where the probabilities based on snapshot 11 to 15 show the lowest absolute and relative error. But again this is relatively high since the proportion of *PHEV* only changes around 0.01% every time period. The same can also be said for type *HEV* shown in Figure 9. Although this does show a declining trend, the proportion of *HEV* rises about 0.05% every time period, making the errors relatively high.

Type *ANDERS*, which showed a stable pattern in the transition probabilities, does have the highest absolute error over all types, but also shows the lowest relative error.

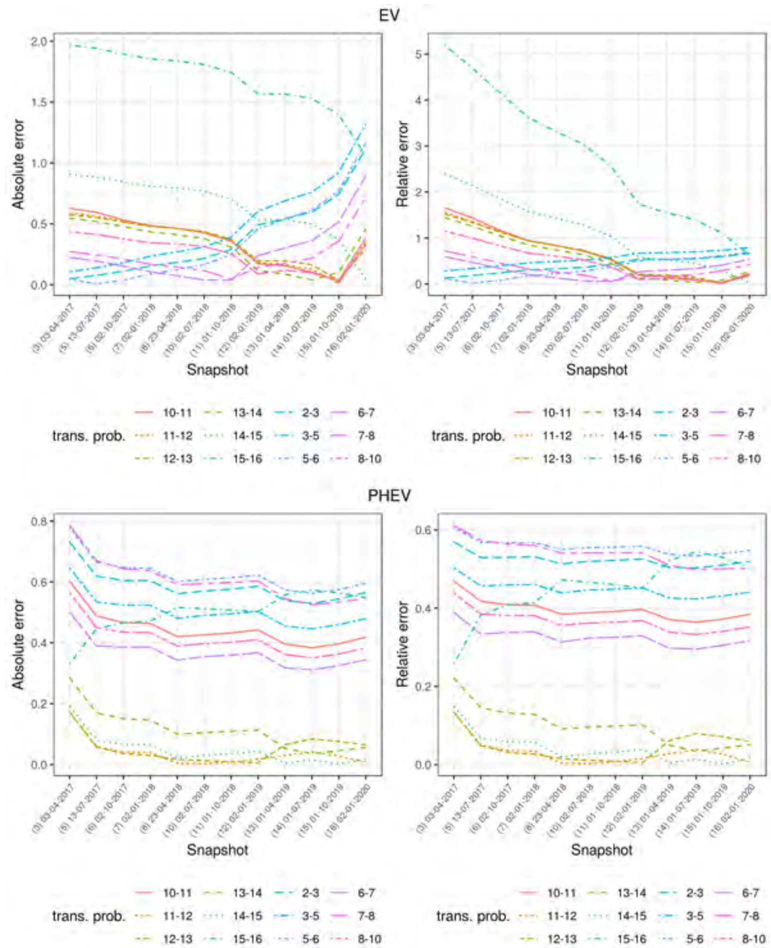

Fig. 8: Prediction errors for 1-step ahead forecast for type EV and PHEV

Based on these results, choosing a transition matrix will be based on the errors for type *EV* and *PHEV* since these are the main focus of this paper and the choice will not have a heavy influence on type *ANDERS* because of its low relative errors. Starting with type *PHEV*, the probabilities based on $11-12$, $12-13$, $13-14$ and $14-15$ clearly outperform the others. These are also probabilities that result in declining errors for type *EV* after October 2018 which is preferable if the proportion of *EVs* is going to follow the same trend after the last snapshot. Therefore, these probabilities will be used to calculate the possible steady-states.

6.4 Steady-State

Calculating the steady-state will tell us what the population of vehicle types will look like when many transitions have passed. Having decided that the transition probabilities based on snapshots $11-12$, $12-13$, $13-14$ and $14-15$ result in

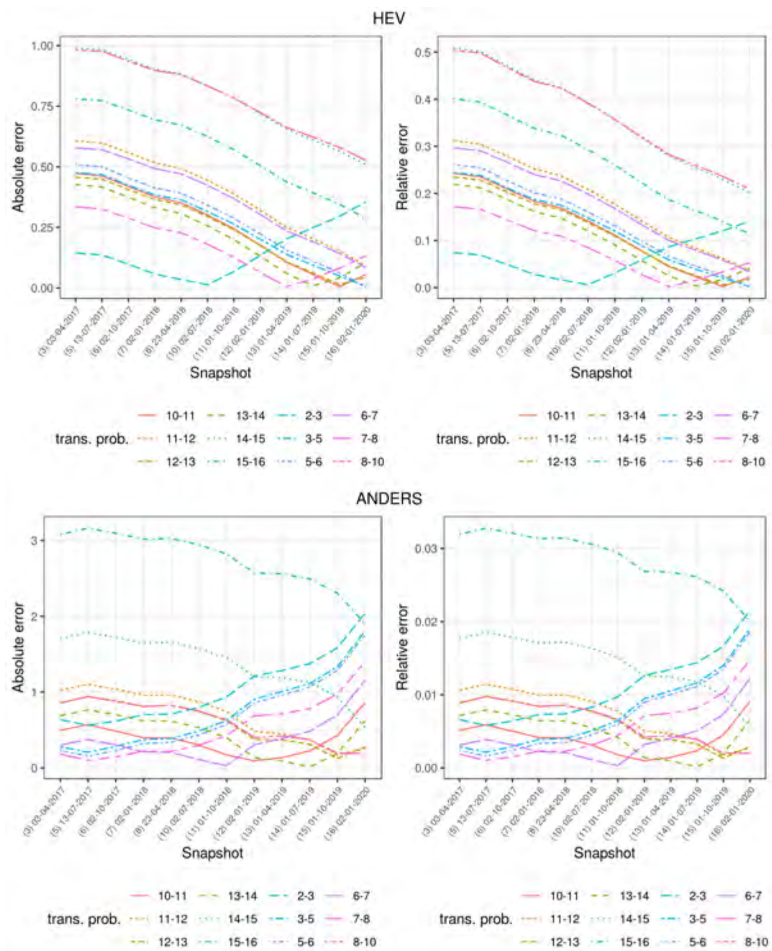

Fig. 9: Prediction errors for 1-step ahead forecast for type HEV and ANDERS

the best prediction performance for type *EV* and *PHEV*, we now need to check if they ensure an ergodic Markov chain since this is necessary for there to be a steady-state. Recall that a Markov chain is ergodic when the states in the system are recurrent, aperiodic and communicate with each other. The chosen transition matrices indicate recurrent states because there are no transient states in this system. There are also no periodic states and all are able to communicate with each other. Hence, the Markov chain is ergodic.

The resulting steady-states are shown in Table 3 along with the percentages of the last available snapshot. As expected, the steady-states for type *EV* range from a minimum of 1.18% to a maximum of 2.19%. One could argue that the latter is more probable since the number of *EVs* seems to be rising. On the long-run the proportion of *PHEVs* does not seem to change much, which can already be seen in the current data, and keeps an average of 1.09% over all π_i.

Vehicle type	Proportions Snapshot 16	π_{11-12}	π_{12-13}	π_{13-14}	π_{14-15}
EV	1.67	1.38	1.50	1.18	2.19
PHEV	1.09	1.10	1.17	1.02	1.09
HEV	2.52	2.63	2.47	2.41	3.14
ANDERS	94.72	94.89	94.85	95.38	93.58

Table 3: Steady-state vectors based on different transition matrices, showing the percentage of vehicle types

For type *HEV* π_{14-15} also produces a higher value than the other steady-states which would also be more likely, since the number of *HEVs* are also rising albeit not as fast as *EVs*. It should also be noted that the probability matrix $14-15$ performed the worst for *EV* and *HEV* but might be better at predicting the long-run. Type *ANDERS* stays more or less the same across all steady-states.

In conclusion, the long-run percentages of these vehicle types, given the four transition matrices, does not seem to change much. It is a reasonable assumption that the number of electric vehicle registrations is highly susceptible to outside stimulants such as government incentives and technological development. This would again emphasize that the transition probabilities are not time independent when there are moments where people are incentivized to use electric vehicles. This makes it difficult to make long-term predictions.

7 Conclusion

In this research paper we tried to gain insights into how certain vehicles are replaced in the fleet of registered vehicles in The Netherlands, with the focus on *EV* and *PHEV* vehicles, by using a discrete-time Markov chain. We did this by comparing 13 snapshots with vehicle registrations from the RDW and making the explicit assumption that any changes on a zip code 6 level are made by the same individuals.

When looking at the single transitions, it became apparent that Tesla and the Mitsubishi Outlander were popular choices as replacements and Volvo users tend to stick to their own brand. The transition probabilities based on all found transitions tend to fluctuate through time, which is unfortunate when using Markov chains because these need to be time independent. Type *ANDERS* does show stable transitions probabilities and makes up the bulk of the total number of transitions.

All 12 transition probability matrices were used to predict 1-step ahead for each snapshot and were evaluated using the absolute error and relative error. The predictions for vehicle type *ANDERS* performed the best since this group changes the least when compared to the other groups. The errors for type *EV* show a turning point in October 2018 when the number of *EVs* started rising. For type *PHEV* there was a clear distinction in performance where the later transitions had the lowest errors, with the exception of the probabilities based on snapshots $15 - 16$, which seems to perform the worst for all types. From the possible transition probabilities, the 4 best performing were chosen to calculate the steady-state vector π.

Using a discrete-time Markov chain to predict vehicle type proportions does produce good results for type *ANDERS* since this group has the most observations and shows a clear pattern through time and for type *PHEV* since the numbers of this group do not show large fluctuations through time. Type *EV* however does fluctuate very around October 2018 making previous transition matrices obsolete when calculating predictions. Since the number of *EV* and *PHEV* registrations will be sensitive to outside stimulants, such as government incentives, these numbers will keep fluctuating which will not work well with a discrete-time Markov model.

8 Glossary

- Electric Vehicle (EV) - A car that uses one or more electric motors and is powered by an on-board battery pack. They can be recharged by plugging it into an external source of electricity.
- E-mobility - Electric mobility.
- Hybrid Electric Vehicle (HEV) - A car that uses an electric motor and internal combustion engine. They can not be recharged from an external source of electricity and the battery is charged using different technologies. Examples of these are regenerative brakes and using the internal combustion engine to generate electricity.
- Plug-In Hybrid Vehicle (PHEV) - A car that uses an electric motor and internal combustion engine. They can be recharged by plugging it into an external source of electricity.
- RDW - Insitute that registers all motorized vehicles and driving licenses. The RDW checks if all vehicles and drivers meet government standards.
- RVO - Rijksdienst voor Ondernemend Nederland; Stimulates enterprising Netherlands with sustainable, agricultural, innovative and international business. They do this by giving grants, finding business partners and meeting law and regulation requirements.

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A Appendix

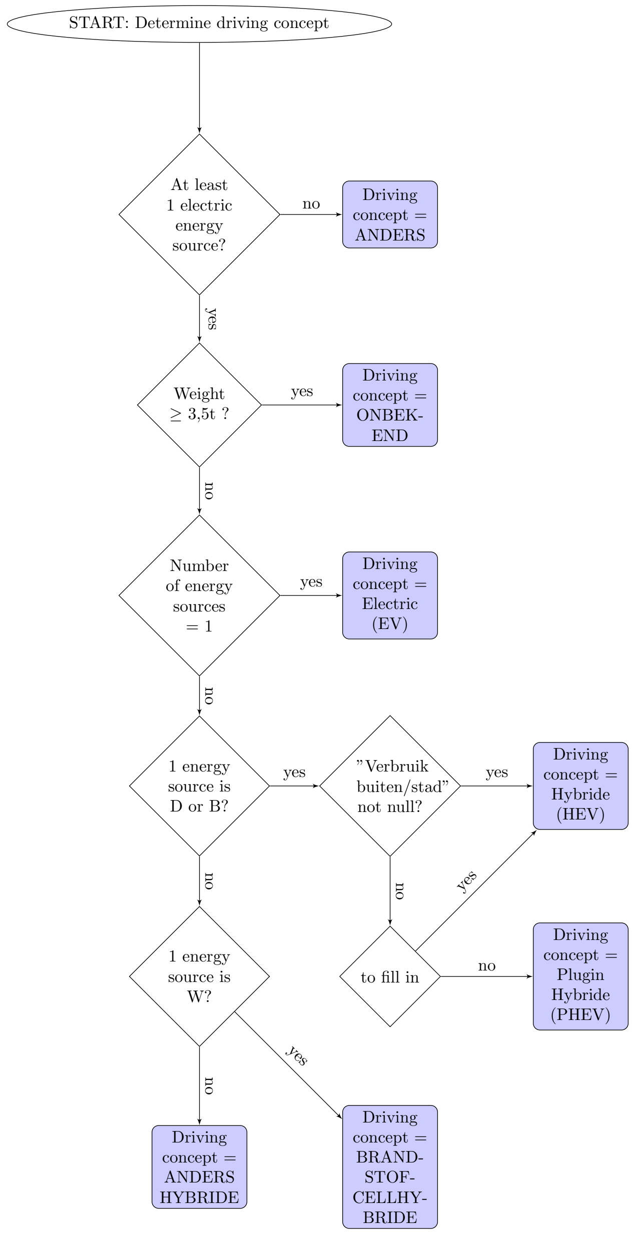

Fig. A.1: RVO flowchart for determining vehicle types

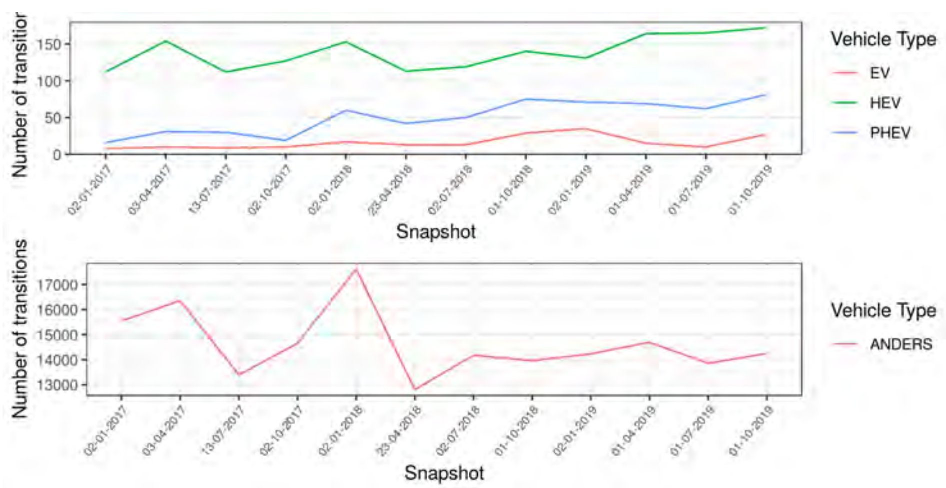

Fig. A.2: Total number of transitions found