Predicting the Impact of Battery Development on Electric Vehicle Adoption

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Abstract— **This paper addresses the question of how change in battery parameters will influence electric vehicle (EV) adoption in the Netherlands. The parameters researched were cost and energy density, as they play a key role in influencing the total cost of ownership (TCO), range and acceleration of EVs. This model uses learning curves to predict the price developments of batteries. Apart from battery parameters, EV adoption is also influenced by various other factors such as buying behavior of people, charging infrastructure, and driving patterns. Thus, the developed battery cost model is implemented into an agent-based EV adoption model and the impact on EV adoption is researched. The results show that with a drop in battery prices, over 50% of the sold vehicles after the year 2028 will be EVs in a represented neighborhood of the Netherlands. However, the model does not consider the effect of battery life degradation.**

I. Introduction

Over the last few decades, temperatures around the globe have been rising due to an increase in greenhouse gas emissions from various sectors [1]. 2015 has been recorded as the hottest year ever witnessed on Earth [2], and the main reason for this is the burning of fossil fuels for generation of energy. Scientists are "95% certain that humans are the main cause of global warming which will lead to high to very high risk of severe, widespread and irreversible impacts globally" [3]. Hence, the switch from fossil fuels to renewable forms of energy needs to be of highest priority. The transportation sector contributes to 14% of the global greenhouse gas (GHG) emissions of which road transportation has been the largest contributor from 1970 to 2010 [4]. Therefore, it is of great relevance to focus the research primarily towards sustainable methods of power generation for road transport.

In contrast to Internal Combustion Engine (ICE) vehicles, Electric Vehicles (EVs) boast of zero tailpipe emissions. Additionally, the electricity required to charge EVs can be obtained from renewable sources, making them an excellent choice for transportation as far as reducing GHG emissions is concerned. Also, electric powertrains boast of an efficiency of 80-90%, compared to 25-30% that is seen in conventional ICE vehicles. Hence, increasing the EV market share will be a significant step towards sustainable transportation.

In spite of being more efficient and less hazardous towards the environment, EVs have not replaced ICE vehicles in the road transport sector. There are several reasons for this such as high initial cost, range anxiety, lack of charging infrastructure, charging durations, et cetera. Crucial factors like initial cost, range, and charging speeds of EVs can be altered by the battery pack, thus making the battery one of the most influential components of an EV.

Fig. 1 shows that the battery pack comprises of 35-50% of the total cost on an EV [5]. By understanding how the battery prices will develop over time, it is possible to get a good idea of the purchase cost and Total Cost of Ownership (TCO) of EVs in the future. Since costs are one of the biggest factors, predicting battery prices is valuable information for voters, activists, and journalists who are interested in moving the status quo towards sustainable transportation.

Apart from the prices, the developments in battery characteristics such as the gravimetric energy density and the specific power play a role in the adoption of EVs. These characteristics vary depending on the type of battery chemistry. For the remainder of this paper, energy density refers to gravimetric energy density unless otherwise stated. Energy density of batteries is defined as the amount of energy that can be stored per kg. The Li-ion chemistry namely lithium nickel cobalt manganese oxide (NCM) and lithium nickel cobalt aluminum oxide (NCA) have the best combination of high energy density and specific power, making it ideal of electric vehicles [6].

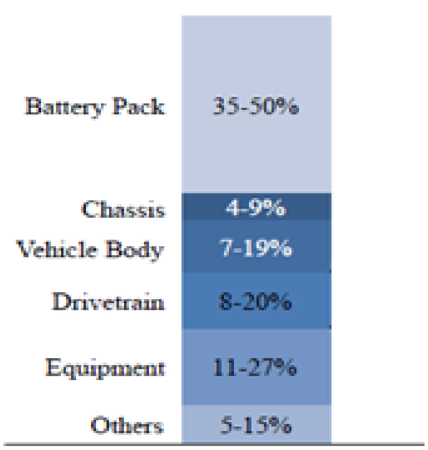

Fig. 1. Cost structure of EVs. [5]

In the past, EVs were not feasible because of the low energy densities batteries used to posses. E.g. To produce an EV with a range of 200 km with a lead-acid battery would have been impossible. Since it has an energy density of 40 Wh/Kg, the weight of the lead acid battery pack of the EV would weigh 1.5 tonnes. To put it into perspective, the battery pack would have to be the size of a Rhinoceros to have enough power to drive 200 Km. Hence, the energy density plays crucial role in making the battery suitable for automotive applications. On the other hand, specific power can determine the high acceleration and fast charging capabilities of an EV. When compared to re-fuelling of ICE vehicles, EVs are considerably slow, leading to long waiting times for charging. This makes it inconvenient for a driver when the car runs out of energy. However, if the batteries have high specific power and available infrastructure for fast charging, then EVs can challenge and even surpass ICE vehicles in the future. Another important aspect of the battery is its degradation. Different components of the battery undergo different aging mechanisms such as SEI formation and electrolyte decomposition, structural transformations, current collector corrosion, and metal dissolutions from electrodes [7]. The main reasons for these degradation mechanisms are the depth of discharge and operating temperatures [8][9]. However, good battery management systems have shown that these effects can be controlled.

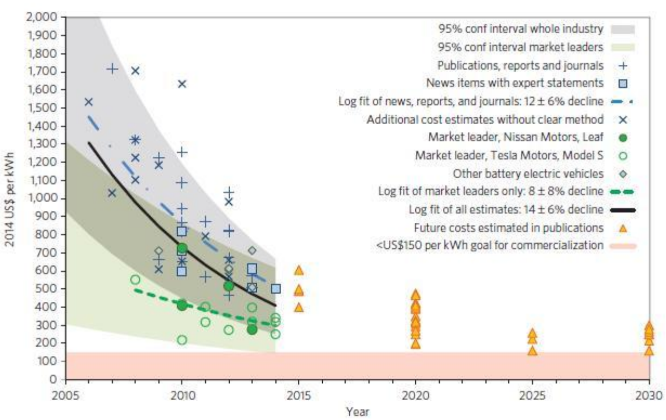

Fig. 2 Battery price forecast [10]

All the above factors related to the battery indicate that EVs will breakthrough into the automotive market but there are very few EV adoption models that take the battery parameters into consideration. The research in [11][12][13] focuses on modeling battery prices in detail by calculating the cost of all the components within the battery cell such as the anode, cathode, current collector, separator, and electrolyte. [10] models a learning curve to forecast battery prices till the year 2030. Aging mechanisms that occur in Li-ion batteries during storage or cycling are described in [7][14][15]. A lifetime prediction model is developed in [16] based on different factors such as State-of-charge (SOC), Temperature, Depth of discharge, and C-rating. [17][18] explain energy consumption models that calculate real-time energy consumption of EVs. An interesting perspective of looking at car-based transportation as a socio-technical system and how interactions within this system can lead to EV adoption is explained in [19]. Agent-based modeling (ABM) is a comprehensive way to model socio-technical systems [20]. [21] and [22] use ABM approach to simulate the development of charging infrastructure while [23] uses ABM to evaluate the interdependencies of manufacturers, consumers, and governmental agencies to simulate diffusion of alternate fuel vehicles.

To understand how the transition to sustainable transportation needs to be made and to get a glimpse as to how it might happen, building a dynamic model that simulates EV adoption is necessary. Since, the battery is an influential component of an EV in terms of cost and other factors, it must have an impact on EV adoption. Thus, the research question that is answered in this paper is:

"*How can we predict the impact of battery developments on EV adoption?*"

As discussed above, there are models which are very detailed in one particular aspect of the battery and other agent based models that speak about EV adoption without taking into consideration battery developments. This paper answers the above research question by developing a battery cost model as battery costs have a big impact on the cost of an EV. This battery model is then incorporated into an agent-based model for EV adoption in which the change in EV sales can be observed with change in battery parameters.

This paper is structured as follows: Section 2 describes existing models that predict battery costs and calculate energy consumption of EVs. Section 3 describes the methodology behind the battery cost model. In section 4, a brief introduction of the EV adoption model is explained along with the methodology used to calculate range and motor power required based on battery and vehicle specifications. The analysis of different resulting scenarios is elucidated in Section 5. Finally, the results will be summarized in Section 6, followed by the scope for future work in section 7.

II. EXISTING MODELS

A. *Battery cost models*

The battery cost model in [24] is called the Battery Performance and Cost model (BatPaC) which predicts the price of batteries. In the BatPaC model, the first step involves calculating the battery performance that is required by the user. To calculate this, various cell and battery pack design formats are taken into consideration. However, it is concluded that the amount of material used for the electrodes, capacity, electrode area, and number of the cells have the largest influence on cost. Changes in type of assembly between cylindrical cells and prismatic cells have a very small influence on the cost. Hence, prismatic cells are chosen as the design for the calculations. Different types of Thermal Management systems are also modeled in detail. Now, the user is asked to enter parameters such as battery power, vehicle range, peak voltage, cell capacity etc. based on his/her requirement. The result that is obtained is the dimensions, mass, volume and material requirements for the entire battery pack. The output from the design model is used to calculate the raw material costs, and then the cost of manufacturing is added to obtain the unit cost of a battery pack. Additionally, the costs for battery management system and thermal management are included to determine the total cost of the integrated battery pack that is sold to the OEM [24]. This detailed bottom-up approach of the BatPaC model ensures high accuracy in cost modeling as every component of the battery is taken into account. It gives a precise cost breakdown of the entire battery pack. Thus, the accurate estimates made by the BatPaC model can serve as reliable guideline when modeling battery costs. However, the time and resources needed to make such a detailed model are very high.

A relatively simpler model is described in [12], which also employs the bottom-up approach considering cost of raw materials, manufacturing and overheads. It assumes the cell structure to be prismatic pouch as in the case of BatPaC model. The cost model in [12] is based on specific charge and operating potential of active materials, considering the price of the individual components. However, the cost of pouch packaging and electric connection is neglected. The result produced in the model is the cell cost in terms of dollars per kilowatt-hour of energy, which is split up into the cost of raw materials (anode, cathode, electrolyte, current collector and separator), process and overhead. It is observed from this result that the cost of the cathode has the largest influence on the cost amongst all the raw materials. Apart from the cost, gravimetric energy density for cells with different anode chemistry is also calculated. The calculations are extrapolated to convey the benefits of such a switch on the automotive industry, if implemented on a large scale. However, this paper does not show how the trend in battery prices will follow in future.

[10] forecasts Li-ion battery prices until the year 2030 by modeling a learning curve as shown in Fig. 2. This learning curve is based on learning rates seen in battery cost development in the automotive industry. This method of forecasting battery prices is much faster and requires lesser resources than the bottom-up modeling seen in [24]. However, there is a compromise on the accuracy of forecast. E.g. according to [10], the forecasted price of Li-ion batteries for market leaders like Tesla is \$250/kWh in 2017, but recent statements from the CTO of Tesla, Mr. J.B Straubel, suggest that the battery prices are \$190/kWh in 2017. Thus, a more aggressive forecast is needed.

B. *Energy consumption models*

[17] uses linear regression and proposes three models that predict the energy consumption of EVs. All the three models proposed in this paper use the vehicle dynamics equation as the basis of their modeling. The goal in [17] is to make a relation between kinematic parameters of the vehicle and its energy consumption. The first model in [17] uses simple input parameters such as travel time, distance, and temperature. The second model uses detailed real-time acceleration data, and the third makes use of micro-trips. Understanding the energy consumption of EVs can help in modeling the range accurately as there is a straightforward link between energy consumption and range. The disadvantage of creating an energy consumption model based on real-time data is that this data must be measured, which takes time.

[18] uses a neural network framework to estimate energy consumption of EVs under real-world driving conditions. The neural network concept helps in categorizing different road types and levels of traffic congestion. Four road types and three levels of traffic congestion provide a comprehensive setup for accurate real-time measurements. The neural network has a list of input variables which include average speed of vehicle, maximum speed, maximum and minimum acceleration, number of stops per km et cetera. With this recorded vehicle data, energy consumption is predicted using battery terminal voltage, current and average speed of an EV.

In the remainder of this paper, a battery cost model based on the combination of the methodologies adopted in [10] and [12] is developed. This model is incorporated into an agent-based model for EV adoption while range and power calculations are made using the vehicle dynamics equation explained in [17]. This EV adoption model is elucidated in section 4.

III. Battery Model Methodology

The Top-Down approach takes into account the total expenditure on a particular product and divides it by the total number of units to obtain the unit cost. This approach can be easily implemented when there is plenty of monetary data available. The calculations involved in this method are rather simple, and thus, the effort and time required to determine unit costs are low. However, there are two main drawbacks to this approach. The first limitation is that the parameters influencing the unit cost are not identified by this approach. This renders the approach ineffective to accurately predict the changes in price over time, which is the second limitation. Consequently, forecasting battery prices accurately is challenging without information regarding the parameters that affect the unit cost.

On the other hand, the Bottom-Up unit cost estimation, or the Engineering Approach, is much more detailed as it identifies all the essential resources for determining the cost of a unit. A summation of all these pertinent resources result in the unit cost. Since a detailed assessment of cost data is done, possible errors and their impacts can be investigated and variations in cost data can be deciphered with greater ease as compared to the top-down approach. These advantages make this approach better suited to forecast the prices of batteries. However, the disadvantage of the bottom-up approach is that it involves higher cost and time to collect data.

A combination of both the approaches can ensure accuracy in predictions in the least amount of time possible. This combined approach is used in this paper. The Top-Down approach, which is the modeling of a learning curve in this paper, ensures that, in short time, a rough estimate of how the battery prices would develop is obtained. The Bottom-Up approach, in this case, is a calculation of raw material costs to ensure that the learning curve values are validated and accurate. Expert predictions are also used to validate the curve. This combined approach used in our model will be explained in this section.

A. *Battery cost learning curve*

1) *Learning Curve theory*

The phenomenon of the learning curve was first observed during World War II when ships and aircrafts were being manufactured [25]. This phenomenon showed that the number of labor hours spent on manufacturing a single unit of a particular product decreases at a uniform rate when the number of units produced doubles [26]. In many cases, labor hours are substituted by production costs [27] [28] . A learning curve for manufacturing progress has the following general equation:

$$Y = Kx^{-\alpha} \qquad (1)$$

where $x > 0$ and K, α are positive constants. Y refers to the costs or labor hours and x corresponds to number of items produced. α is called the learning index [29].

Since 1936, learning curves have been used extensively in different fields [25], most commonly describing random variable distribution or autocorrelation of a random process. It is also used in volatility forecasting, statistical estimation and derivative pricing [30]. An experience curve is a form of a learning curve with small differences. [27] states that, "The notion of the experience curves varies from the more specific formulation behind the learning curve in that it aggregates from individuals to entire industries and from labor costs to all manufacturing costs". Since the entire manufacturing cost is more relevant than the labor costs for this study, we will use the term of experience curve throughout the remainder of this paper. Experience curves have been modeled to predict development in different technologies [10] [27] [28]. Since studies show that costs always reduce as cumulative production increases, albeit at different learning rates, experience curves have been widely used in forecasting prices of new technology.

One such example is shown in the model developed for Photovoltaics in [31]. An experience curve is modeled to show the development of PV module prices from the year 1980-2050, and it is compared with a Bottom-Up cost model to test its reliability. The experience curve shows a reasonably good forecast with respect to the cost model [31]. Another example that used the learning curve approach to predict the costs of an upcoming technology is discussed in [28]. [28] models a learning curve to forecast the mass production prices of Proton Exchange Membrane fuel cells. Nine experience curves are modeled; each represents nine scenarios depending on the rate of improvement of power density and cost reduction speeds of membranes, electrodes, and bipolar plates. The above examples validate the choice of modeling an experience curve to forecast battery prices in this paper. Also, there are recent papers on predicted battery prices [10] [32] that show that the trend is in the form of a power law, which further validates our choice of using experience curve modeling approach.

However, it is very easy to go wrong while modeling these curves. Hence, two approaches to ensure that the experience curves are modeled with sufficient accuracy are considered. The first approach is verifying the modeled curve with expert predictions. Due to its exponential characteristics, the experience curve calculations occasionally lead to very small values that are not realistic [28]. Thus, the minimum value that the costs can drop to needs to be set. The second approach is a bottom-up calculation of the price of raw materials which corresponds to this minimum value that the costs in the experience curve can drop to.

a) Expert predictions to validate the experience curve

As mentioned above, to expedite the process of cost estimation and to obtain an initial idea of the trend of battery costs, expert predictions are taken into consideration. After analyzing predictions from [5][10][12][24][33][34][35][36][37][38], which are made in 2013 and 2014, it is understood that the trend of battery prices showed a steep decrease initially, and then remained fairly constant, similar to a power curve. This flattening of the curve is because the battery prices become very close to the raw material price of the battery itself. Since it is impossible to get lower than the price of raw material, the closer the prices get to the raw material cost, the more difficult it becomes to reduce the price further. To understand if the trend in battery price predictions still holds in 2017, a literature survey is carried out. Unsurprisingly, the same trend is observed but there was a change in the predicted values of costs. UBS and Deutsche Bank predicted in 2013 that the price of batteries would be \$260/kWh [33] and \$225/kWh [34] respectively in 2018, but Tesla announced in 2016 that their batteries will cost \$190/kWh in 2018. Additionally, General Motors made an announcement that the cell cost of the new Chevrolet Bolt will be \$145/kWh in 2019. By considering a factor of 33% for packaging [39], the price of the battery pack becomes similar to that of the Tesla Model 3 [35]. This observation showed that the industry is progressing at a greater rate than what was previously predicted and more radical predictions need to be made.

Finally, an experience curve is modeled to make a best fit along known estimates. A better estimation would have been to take the variable part of the battery price, i.e, the production cost and overheads and estimate that every doubling of production would lead to a decrease in a certain percentage of price. However, this would mean creating a feedback loop between battery price and battery sales, which would consume more time. Hence, for simplicity, it was omitted. It would also mean creating multiple curves for multiple chemistries. Together, they would have created too much of a resource draw while improving the shape only marginally.

B. Learning curve reality check using raw material costs

Now, to achieve the lower bound on the cost of the battery, the raw material costs are obtained using the Bottom-Up cost approach. This approach breaks the battery down into its raw materials; namely the cathode, anode, current collector, electrolyte and separator. The sum of the prices of each of these components result in the cost of raw materials. From [12], it is observed that the cost of the cathode for each cell chemistry plays a major role in determining the cost of raw materials, and thus, a calculation of the cathode cost is done. The costs of the other raw materials used in making the anode, current collector, separator, and electrolyte are taken from [12] and [11]. To determine the price of the cathode, the weight of each material used is calculated, and this weight is multiplied with the cost of the material per kilogram to give the total cost. For example, the cathode of an NCM battery consists of Nickel, Cobalt, Manganese, Lithium and Oxygen. Calculating the weight of Nickel and multiplying it with the cost per kilogram gives the total cost of Nickel. Performing similar calculations for Cobalt, Manganese, Lithium, and Oxygen, and summing up their respective total costs, an estimate of the cathode's costs can be achieved. It must be noted that these calculations are made in terms of price per kWh of energy.

Developments in battery technology are slightly different from other technologies. Usually, when there is an improvement in a particular characteristic of a product, one must pay extra for this. For example, an external hard disk with 1GB storage space will cost lesser than one with 2 GB of storage. However, when it comes to the gravimetric energy density of batteries, it is the opposite. As the energy density increases with advancements in technology, it means that a greater amount of energy can be stored in the battery per unit weight. This characteristic means that to produce 1 kWh of energy, lesser raw materials will be used. In our model, this has an influence on the lower limit, which is the cost of raw materials. Thus, as technology improvements occur in battery chemistry, the price will reduce even further.

C. Battery price prediction

After validating the experience curve with expert predictions and obtaining the minimum to which these prices can drop, an experience curve is modeled from the year 2010 to 2035 with the following equation:

$$Battery\ price = K * (1 + x - c)^{-\alpha} \qquad (2)$$

where,
c = starting year (2010 in our case)
K= Initial battery price in year "c"
x = Current Year
α = Learning index

Using (2), three experience curves are modeled for Li-ion batteries which represent three scenarios- an optimistic fast development, a pessimistic slow development scenario and our best guess. The slow development scenario assumes there will be no new battery chemistry that will enter the market till 2035, but the NCM battery's production process would become extremely mature, such that the price of the NCM battery would be equal to the price of its raw materials along with a small overhead. On the other hand, the fast development scenario makes aggressive predictions about new chemistries such as Li-S entering the market and being mass produced by 2035. The final values of these two curves are in accordance with the raw material prices in appendix, section C, with a small overhead included. The best guess scenario is what we think realistically will be the prices of Li-ion batteries in the coming years.

IV. Adoption Model Methodology

Predicting EV adoption involves understanding complex concepts such as battery price developments, buying behavior of people, types of cars produced by car manufacturers, charging infrastructure available, driving patterns of people et cetera, thus making it a socio-technical system. Modeling the interactions between different aspects with distinct behaviors within a socio-technical system is required to predict EV adoption because it is the interactions between systems that actually happens in the real world. Agent-based Modeling is a technique which models these interactions and behaviors between agents of a socio-technical system [20]. This method can be particularly used for energy networks. As defined in [20], "an agent is an encapsulated computer system that is situated in some environment, and that is capable of flexible, autonomous action in that environment in order to meet its design objectives. It is the smallest element of an agent-based model that is able to perform actions on itself and other agents, receive inputs from the environment and other agents, and behave flexibly and autonomously because an agent consists of both states and rules."

A. Agent-based EV Adoption Model

The Agent-Based Buying Charging Driving (ABCD) model is an agent-based model that comprises of different agents such as battery manufacturer, car manufacturer, car dealer, people, EVs, charge points, charge point operators, municipality etc. and simulates the interactions between these agents. The aim of this ABCD model is to predict the rise of electric vehicles and charging infrastructure in the Netherlands by researching the dynamics between these systems. The ABCD model is divided into different modules that represent the entire eco-system related to electric vehicles. These divisions are made to try and replicate what is happening in reality. The modules comprise of:

- Buying Module: This module describes how a choice is made by a customer to choose either an internal combustion engine (ICE) vehicle or electric vehicle when he/she visits a car dealer. These choices are based on a mixture of monetary and non-monetary factors which are explained in detail in [40] and will be elaborated in this section.
- Charging module: The aim of this module is to model the charging infrastructure rollout and usage in Dutch neighborhoods. [41]
- Driving module: This module focuses on the types of driving patterns that the residents of the neighborhood have.

Since the ABCD model models the buying behavior of people in a particular neighborhood of the Netherlands, and the aim of this research is to see how battery prices affect the adoption of EV in the Netherlands, the effects of incorporating the battery price model into the ABCD model are researched.

The buying module is particularly of interest in this study because it involves interactions between the battery manufacturer agent, car manufacturer agent, car dealer agent and the residents of the neighborhood.

In the neighborhood, residents who do not own a vehicle may visit the car dealer every month. The step of the simulation is set to one month. The number of residents in the neighborhood is fixed to an arbitrary value of 500. All the results that follow in the section V are for 500 residents. It can be scaled up to make it representative of the whole of Holland. The dealer provides the user with choices of EV and ICE models based on the user’s preferences and financial abilities.. In the ABCD model, the choice of cars that the dealer provides are constrained based for simplicity. Three classes of vehicles are available to the customer namely A-Class, C-class and E-class. The choice of class is made based on the income of the customer. After the class is selected, the customer has three options of range to choose from within the chosen class. The choice of range is based on his driving pattern and his range anxiety. The choices of range are directly linked to the size of the battery pack. Larger the battery pack size, higher will be the range of the vehicle. The size of the batteries are chosen based on market survey and is further explained in [40]. After choosing the car class and the range, the final step in the buying behavior is choosing the acceleration. Most customers in reality give preference to how quick they would want their car to be in terms of acceleration time from 0-100 Km/hr. There are three choices of acceleration time for each range. Thus, there are 27 cars (nine from each class) that the consumer can choose from.

B. TCO comparison

After choosing the class, range and power, the total cost of ownership (TCO) needs to be calculated [40]. The motor size contributes significantly to the TCO and the power of the motor is influenced by the total weight of the EV. The battery pack contributes significantly to the weight of the EV [42]. The lighter the battery pack, the lesser motor power is needed to achieve the same acceleration. Thus, the weight of the battery pack has an influence on the cost. In the past, this influence was a lot more prominent. This was because the weight of the battery pack comprised of a fairly large percentage of the total weight of a vehicle. For example, the EV1, which was the first mass-produced electric car, had a 16.5 kWh Lead Acid battery pack that weighed 533 kg when it was first launched in 1996. The battery pack weighed 38% of the entire vehicle's weight. It had a 102 kW motor that could help achieve a 0-100 km/hr acceleration time of 10 seconds. In comparison to the EV1, the Tesla model S 2012 version had a battery pack that weighed 544 Kg but had an 85 kWh battery pack [42]. The battery weight though was only 25% of the total vehicle's weight and it has a 350 kW motor to achieve an acceleration time of 4.5 seconds for 0-100 km/hr. Thus, to achieve a particular acceleration, the motor size needs to be chosen and the motor to be chosen depends on the weight of the battery pack and the rest of the vehicle. However, as the ratio of battery weight to total vehicle weight reduces, the rest of the car starts becoming more and more significant in terms of influence on choice of motor power.

After the motor power, another influence on the TCO is the range of the vehicle. The range of an EV is largely dependent on the size of the battery pack. The higher the capacity of the battery pack, the larger is the range, provided that the battery chemistry stays the same. The battery chemistry has an influence, although limited, on the range through the gravimetric energy density of the battery. As the energy density increases, the amount of energy that can be stored per unit weight increases thus making the batteries lighter. For example, the EV1 with Lead-Acid batteries had an energy density of 40 Wh/kg. With such a low energy density, only a pack size of 16.5 kWh seemed feasible, thus limiting the range. Increasing the pack size would lead to a very heavy battery, which would make the car less attractive. On the other hand, the Tesla Model S with NCA batteries had an energy density of approximately 250 Wh/kg in 2013, thus allowing the manufacturer to incorporate a pack size of 85 kWh for almost the same weight as the battery pack of the EV1. However, the range has a small impact on the TCO because when it comes to choosing the range, the range anxiety of customers plays a larger role as observed in reality. It is difficult to quantify this "feeling of freedom" factor. To understand the implementation of range anxiety in this model, refer to [40]. Since the range of the vehicle is important to the TCO, albeit to a small extent, and also the fact that the range plays a role in the placement of charge points in the neighborhood [41], it needs to be calculated.

The battery prices from the battery model has the largest impact on the TCO calculation of the EV adoption model [40]. These battery prices are used as input by the car manufacturer agent along with the range and motor size. Based on these parameters, the car manufacturer agent calculates the TCO of an EV and compares it with the TCO of an ICE vehicle.

The TCO influences the buying behavior of electric vehicles in the ABCD model. It takes into account the income, acceleration preference, and range anxiety of the customer as is the case in the real world. It performs a TCO comparison as well which helps the customer to make buying decisions. The details of the entire buying module can be understood from [40].

C. Range and Motor power calculation

The range and motor power calculation involves the interaction between two agents of the model: namely the battery manufacturer agent and the car manufacturer agent. The car manufacturer produces three classes of cars - A, C, and E with three options of battery sizes each. These battery sizes are determined after performing a market survey, the sources of which are mentioned in [40].

These values of battery sizes are given to the battery manufacturer from the car manufacturer, along with the weight of the vehicle excluding the weight of the battery pack. Using the values for pack size (expressed in kWh), and the energy density for each year, the corresponding weight of the battery cells in the pack is obtained. The weight for packaging is added to the weight of battery cells to obtain the weight of the entire battery pack. The total EV weight is calculated by adding the total battery pack weight with the remaining vehicle weight which is also obtained from the car manufacturer.

[17] uses a vehicle dynamics equation to calculate mechanical energy required at the wheels for a given driving distance. This vehicle dynamics equation is simplified by making assumptions and is used in our model to calculate energy consumption. The simplification is done due to lack of real-time driving data. The energy consumption equation from [17] is modified as follows:

$$E = \frac{1000}{3600}\left[mgf + 0.0386(\rho C A v^2) + (ma)\right] \qquad (3)$$

Where,
E = energy consumption [Wh/Km]
m = total mass of vehicle [Kg]
g = 9.8 m/sec^2
f = Vehicle co-efficient of rolling resistance [-]
ρ = air density [Kg/m^3]
C = Drag co-efficient [-]
A = Vehicle cross-sectional area [m^2]
v = vehicle speed [km/hr]

a = acceleration

The range for every battery pack size is thus obtained by dividing it with the corresponding energy consumption. Once this is done, nine options of 0-100 km/hr acceleration times are set by the car manufacturer- three in each class. To achieve the desired acceleration time, the power of the motor has to be determined. This power is calculated using the following formula [43]:

$$P = \frac{m.v^2}{\mathrm{t}} \qquad (4)$$

where,
P = power required
m = total vehicle mass
v = 100 km/hr
t = acceleration times (sec)

D. Battery Power calculation

It is obvious that the maximum motor power ($P_{max,motor}$) has to be lesser than the maximum battery power ($P_{max,battery}$) since the battery is the power source.

$P_{max,battery}$ is calculated using the internal resistance, maximum discharge current and battery voltage of a single cell. For more details on this calculation, refer to section B of the appendix. $P_{max,battery}$ for each battery pack size is calculated and compared with the corresponding $P_{max,motor}$ that is chosen by the customer in the ABCD model. If $P_{max,battery} > P_{max,motor}$, the car manufacturer will continue to produce this vehicle and offer it as an option to the customer. If $P_{max,battery} < P_{max,motor}$ then the car manufacturer agent "kills" that particular vehicle and does not offer it as a choice to the customer. E.g. for an EV with a 30 kWh battery pack to achieve an acceleration time of 4 seconds from 0-100 km/hr might be difficult because it would be unable to sustain a discharge rate that is high enough to meet the power requirements of the motor.

E. Model Calibration

The model needs to be calibrated to make sure that the output values are realistic. Even though we do not know exact number of EVs that will be sold till 2035 in the Netherlands, it is important to check that the outputs are not extraordinarily disruptive. A similar case also applies for the energy consumption of an EV. Since there is a lack of real-time data for the acceleration value used in (3), this value was calibrated to ensure that the energy consumption for C-class vehicle matched the average value in [44] and the E-class value for energy consumption matched the average value in [45]. Since there are not many A - Class electric vehicles on the road at the moment, there was a lack of data to calibrate it with. Thus, it was assumed that the energy consumption values would follow the trend which showed that lower the battery pack size, lower is the energy consumption per km driven.

F. Assumptions

- Weight of packaging the cells into a battery pack is taken as 44% of the weight of battery cells. This value was calculated from data available for Tesla model S [42]. It was also verified by expert's opinion.
- The energy consumption equation adopted from [17] considers battery-to-wheel scope and corresponds to the energy drawn from the battery. Therefore, the losses in the energy supply chain prior to the battery are not considered as they do not impact the range of the EV. [17]
- Vehicle parameters such as vehicle cross-sectional area, drag co-efficient, co-efficient of rolling resistance, and total mass of vehicle are required in (3). For E-class vehicles, the Tesla Model S parameters are taken. For C-class, the Nissan Leaf data is used [46]. The values for A-class cars is taken from the VW golf. This is because there are no existing A class EVs in the market.
- Air density is taken to be 1.2 kg/m^3 as the ABCD model is for the Netherlands which is relatively on par with sea level.
- The vehicle speed used in (3) is assumed to be 50 km/hr because top speeds in most neighborhoods in the Netherlands is 50 km/hr.
- Depth of discharge and temperature play a big role in cycle life. For now, we have neglected degradation effects and given a life span of 10 years to the NCA/NCM battery based on [45]
- Range is affected by temperature and Depth of discharge. For the sake of simplicity, these are not taken into account for range calculation.
- Since cells for Tesla are custom-made by Panasonic, it is hard to get exact details about the data of the cell. The 18650 BD panasonic cells data are used instead for battery calculations [47]. We assume that this cell is the closest to the Li-ion cells used by Tesla.
- The battery prices developed in this model are whole sale battery prices that OEM's pay to battery manufacturers.
- Taking into consideration the Euro-dollar conversion rate at the time of formulating the results, it is assumed to be \$1= 0.9€.
- The annual production numbers of batteries can influence the cost greatly in the future. However, in this model, the effect of the number of batteries that will be produced is taken as a constant.
- The cost for packaging the battery pack is assumed to be 20% of the cell cost. [24]

V. Scenario Analysis and Results

A. Battery prices

Fig. 3 shows the result of the battery model. Battery price experience curves were modeled that show the development of battery prices in €/kWh based on (2). The model starts in the year 2010 with an initial battery price of €750/kWh. Three scenarios namely the slow development, best guess, and fast development are modeled with learning indexes of 0.58, 0.67, and 0.78 respectively.

The slow development scenario assumes that the manufacturing processes of the NCM/NCA chemistry matures significantly and no new chemistry will enter the market.

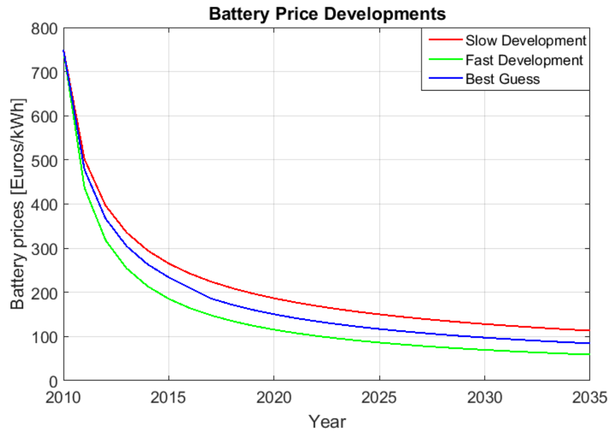

Fig. 3. Battery price developments

Also, there will be no alteration in the anode materials which prevents the cost from reducing further.

The fast development scenario makes aggressive predictions about new chemistries such as Li-S entering the market and being mass produced in 2035.

The best guess assumes that there will be developments in anode materials such as shifting from a graphite based anode, to a Silicon composite anode and eventually to Ultra-thin Lithium metal as anode. This will significantly improve energy density and safety while bringing down the costs. Tesla's current batteries are already using silicon-composite anodes in the 2170 battery cells used in the Tesla Model 3.

All the three scenarios add a 14% overhead to the corresponding raw material costs mentioned in section C of the appendix to obtain the final battery costs in 2035.

These experience curves are the basis for the scenarios described in the following sub sections.

B. *Influence of battery price development on EV sales*

1) *Total EV sales*

Fig. 4. shows the impact of different battery price development rates on EV sales. In all three battery development scenarios, rate of increase in EV sales from 2010-2015 was low due to high battery prices. Post 2016, there is a linear increase in the number of EVs sold. There is a difference of 107 in cumulative EV sales between the slow development and fast development scenarios at the end of 2035. Considering that the neighborhood under consideration has only 500 residents, this difference is quite significant.

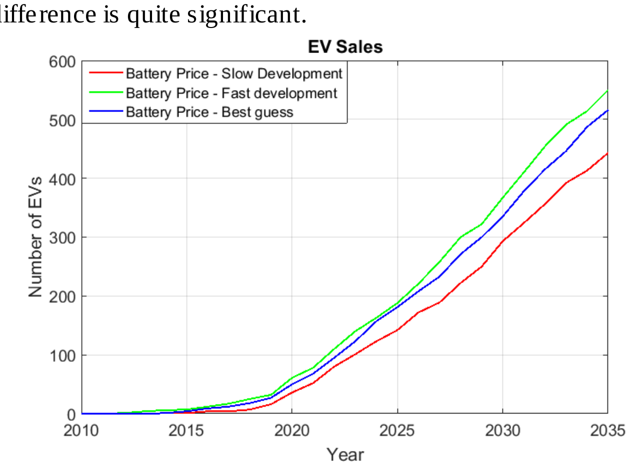

Fig. 4. Cumulative EV sales based on battery price developments

2) *Market share- EV Vs ICE*

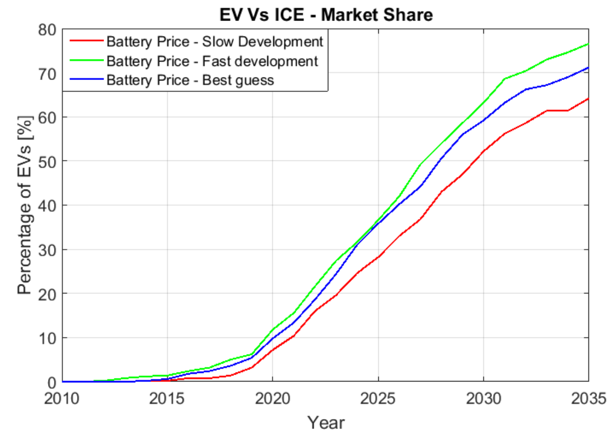

Fig. 5. Market share on EVs

Fig.5 shows the market share of EVs as a percentage of the total number of vehicles in the neighborhood. The graph shows that the market share of EVs is above 50% after 2030, irrespective of the rate of battery price developments.

3) *Choice of battery size within a particular class*

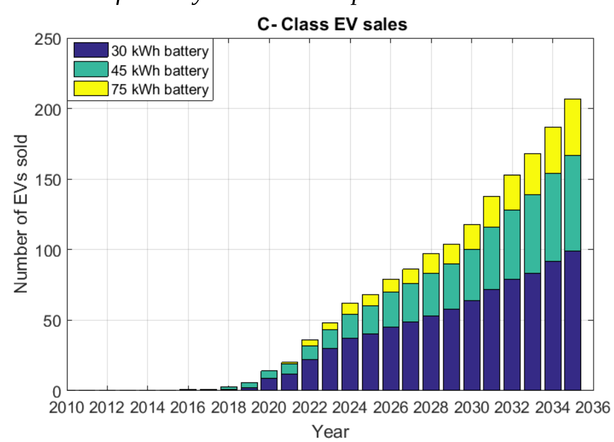

Fig. 6. C-Class EV sales for slow development of battery price

Fig. 6 shows the sales of the different battery pack sizes of C-Class EVs. If people with high range anxiety want to choose between an EV and an ICE vehicle within C-class, they are most likely to choose the largest battery pack available. This will not be possible unless the prices drop significantly enough to make the TCO of an EV cheaper than that of the ICE. This scenario shows how as the battery prices drop, people with large range anxiety will start choosing EVs over ICE. The slow development battery prices are used in this scenario so that this dynamic is made more pronounced. Till the year 2021, no 75 kWh batteries are sold due to high battery prices. After 2022, battery price reduces the TCO of EVs below that of a comparable ICE vehicle. Thus, the C-Class EV with a larger battery pack starts selling more after the battery prices drop to €169/kWh.

C. Breakthrough scenario- New battery chemistry enters market in 2025

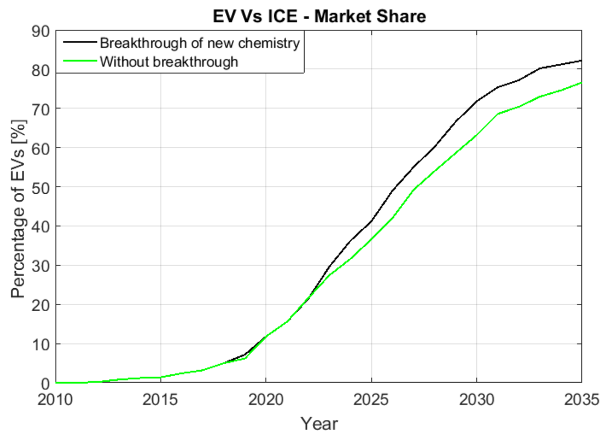

Fig. 7. Effect of new battery chemistry breakthrough on EV market share

New battery chemistries such as Lithium Sulfur (Li-S) and solid state batteries have been known to have extremely high theoretical energy densities [48] [12]. The cost of raw materials of Li-S batteries are low making it a promising alternative in future. However, at the moment there are issues regarding the cycle life and large volume expansions which are preventing it from entering the market. Fig. 7 considers a hypothetical situation which assumes that the issues related to Li-S and solid state batteries get solved by 2025 and this battery enters the automotive market. Due to its high energy density, the batteries become much lighter, thereby reducing the weight of an EV drastically. An energy density of 600 Wh/Kg is assumed in the 2025 based on expert opinions and is made to gradually increase till 1100 Wh/Kg in 2035. This value is still only half the theoretical maximum energy density of Li-S, which boasts of a maximum energy density of 2400 Wh/Kg. For this scenario, the fast development battery prices are used. The only difference between the breakthrough and no breakthrough scenarios is the increase in energy density. The results in Fig. 7 show that there is a noticeable jump in the market share of EVs from the year 2025, i.e., from the year the breakthrough happens.   Fig. 8 shows the difference in the number of EVs sold when the breakthrough of a new chemistry takes place.

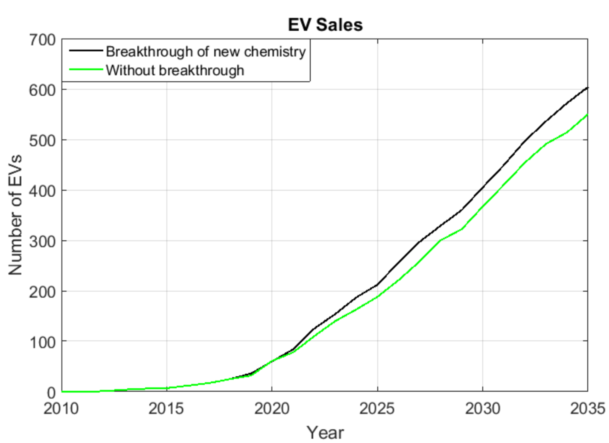

Fig. 8. Effect of new battery chemistry breakthrough on EV sales

VI. CONCLUSIONS

Predicting EV adoption requires a holistic understanding of interactions between different subsystems related to it. Since the battery is one of the most important components of an EV, it must be accounted for while making EV adoption models.

In this paper, battery prices are forecasted using the learning curve approach. These battery costs, along with calculations for range and power were implemented into a battery manufacturer agent of an agent-based model to observe the impact on EV adoption.

The battery model predicted that the battery prices would drop to below €100/kWh by 2030. The EV adoption model predicted that there will be a market share of 35% by 2025 and eventually 71% by the end of 2035. Also, it was inferred that the battery costs will have to reduce below €160/kWh to make people with high range anxiety choose EVs over ICE vehicles as bigger battery packs will become affordable. Finally, breakthrough of new chemistries can increase the market share of EVs further by 5-8%.

VII. DISCUSSION AND FUTURE WORK

In the current model, the learning index assumes for every doubling of production there will be a drop in costs by a certain percentage. However, this is not the most accurate way of modeling. Since the agent-based model has a car manufacturer agent and a battery manufacturer agent, a feedback loop can be created such that the EV sales can also drive battery prices. The effect of economies of scale can be studied by including this dynamic.

In this model, it is assumed that an EV will last for a period of ten years and does not take into account the degradation of the battery. This dynamic can be added by modeling an S-curve which shows remaining state of charge versus Km traveled similar to the one seen in [41]. Based on expert opinion, it was found that an EV retains 80% of its original capacity after 500,000 km. This can create a very interesting second hand market scenario if battery degradation is implemented. E.g a new Tesla Model S 75 has a range of 400 km. After covering 500,000 km, it will still have a range of 320km which makes it very competitive against a new C-class EV with close to the same range.

Implementing battery chemistries with different discharge rates can add an interesting dynamic to the model. E.g. Lithium Titanate or Lithium Iron Phosphate batteries have the possibility of charging and discharging at very high C-rates. This make these chemistries an interesting choice for heavy duty applications such as trucks. Also, due to the high C-rates, these batteries can charge at much higher speeds as compared to NCM batteries. In the ABCD Model, both chemistries can be offered to the consumer and depending on the requirement, a choice between the chemistries can be made.

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IX. APPENDIX

A. Bottom up calculation for cathode raw material cost

1) Theoretical maximum amount of Lithium that can be extracted from 1 Kg of Li_2CO_3

```
% Molar masses

m_Li = 7; % g/mol

m_C = 12; % g/mol

m_O = 16; % g/mol

m_Ni = 58.693; % g/mol

m_Co = 58.933; % g/mol

m_Mn = 54.938; % g/mol

m_Li2CO3 = m_Li*2 + m_C + m_O*3; % molar mass of Li2CO3 in g/mol

nu_Li2CO3 = 1000/m_Li2CO3 ; % 1000 grams divided by molar mass gives number of moles of Li2CO3 in 1kg of Li2CO3

nu_Li = 2*nu_Li2CO3; % number of moles of lithium in 1 kg of Li2CO3

M_Li = nu_Li*m_Li ; % Theoretical maximum amount of lithium in grams
```

2) Amount of each material required for 1kWh of energy

```
Energy = 1000; % in Watt hour

Energy_J = 3600*1000 ; % in Joules

V = 3.6 ; % operating voltage of NCM battery

Q = Energy_J/V ; % charge in Coulumb

F = 96485 ; % Faraday's number in C/mol
```

3) For normal LiNi0.33Mn0.33Co0.33O2

```
int_factor_NCM = 1/(0.9-0.5) ; % intercalation factor for normal NCM battery 0.5<x<0.9

Nu_Li = Q/F * int_factor_NCM ; % number of moles of Lithium in NCM battery

Nu_Ni = Nu_Li * 0.333 ; % number of moles of cobalt, Ni and Al is 0.333x number of moles of Lithium as per the chemistry

Nu_Co = Nu_Ni ;

Nu_Mn = Nu_Ni ;

Nu_O = Nu_Li*2 ; % number of moles of oxygen

% Hence, weight of each material required to produce 1kWh energy is :

wt_Li = Nu_Li*m_Li ; % in grams
```

```
wt_Ni = Nu_Ni * m_Ni ; % in grams

wt_Co = Nu_Co * m_Co ; % in grams

wt_Mn = Nu_Mn * m_Mn ; % in grams

wt_O = Nu_O * m_O ; % in grams

total_wt_cathode = wt_Li+wt_Ni+wt_Co+wt_Mn+wt_O
; % in grams
```

4) For Lithium Rich - NCM batteries

```
int_factor_LRNCM = 1/(1-0.5) ;

Nu_Li = Q/F * int_factor_LRNCM ; % number of
moles of Lithium in NCM battery

Nu_Ni = Nu_Li * 0.333 ; % number of moles of
cobalt, Ni and Al is 0.333 times the number of
moles of Lithium as per the chemistry

Nu_Co = Nu_Ni ;

Nu_Mn = Nu_Ni ;

Nu_O = Nu_Li*2 ; % number of moles of oxygen

% Hence, weight of each material required to
produce 1kWh energy is :

wt_Li = Nu_Li*m_Li ; % in grams

wt_Ni = Nu_Ni * m_Ni ; % in grams

wt_Co = Nu_Co * m_Co ; % in grams

wt_Mn = Nu_Mn * m_Mn ; % in grams

wt_O = Nu_O * m_O ; % in grams

total_wt_cathode = wt_Li+wt_Ni+wt_Co+wt_Mn+wt_O
; % in grams
```

To find the raw material cost of cathode per kWh, multiply the weight of each material to the cost of each material.

B. Maximum Power that can be drawn from the battery pack

Using data of 18650 BD panasonic [47] cells, we get internal resistance as 0.035 ohms.

$$V_{battery} = V_{eq} - r.I \quad (4)$$
$$P = IV_{battery} \quad (5)$$

From (4) and (5), we get

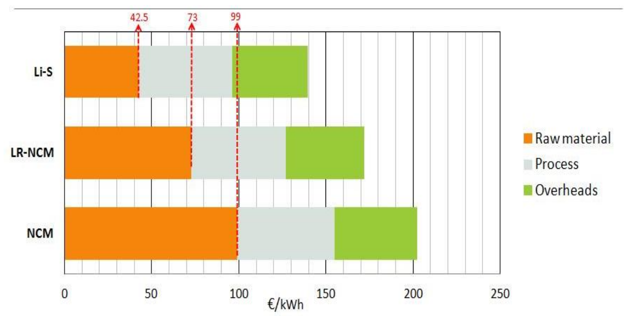
$$P = I\,(V_{eq} - r.I\,) \quad (6)$$

We know that $\frac{dP}{dI} = 0$
Therefore ,

$$I = \frac{V_{eq}}{2r}$$

Using the above formulas, power for each panasonic 18650 BD cell was found to be 92.57 W. Dividing total pack capacity by the cell capacity gives you number of cells. Multiplying the number of cells with the power for one cell gives you the maximum power the can be delivered by the battery pack.

C. Cell costs of batteries



Source: Adapted from "Rechargeable Batteries: Grasping for the Limits of Chemistry" by Petr Novak, Journal of Electrochemical Society, October 2015