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How will future BEV models develop? Market potential of different battery technologies assessed by a ML-based manufacturer agent

Samuel Hasselwander *, Julian Rettich, Stephan Schmid, Tjark Siefkes

German Aerospace Center (DLR), Institute of Vehicle Concepts, Pfaffenwaldring 38-40, Stuttgart, 70569, Germany

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ABSTRACT

The ramp up of battery electric vehicles is already in full swing, with multiple countries having implemented regulations to defossilize their vehicle fleets. This is leading to a growing number of vehicle models that are becoming increasingly diverse, with even fundamental differences in battery chemistry. However, it is important to understand which energy storage technology will be used in future vehicles in order to recognize and avoid dependencies on raw materials or supply chains at an early stage.

By developing a machine learning based manufacturer agent trained on historic vehicle data from models available in Germany and a comprehensive technology and component database, we show that it is possible to predict the market potential of bottom-up calculated future battery electric vehicle models. Our findings align with the current trend towards diversifying vehicle models through the adoption of various cell chemistries. The results indicate that vehicles equipped with lithium iron phosphate or even sodium-ion batteries, particularly those utilizing cell-to-pack technology, demonstrate significant market potential in the near future, especially for small vehicles.

1. Introduction

Due to their contribution to climate change, conventional internal combustion engine vehicles (ICEVs), which primarily rely on fossil fuels, must be replaced with climate-friendly alternatives [1,2]. Battery electric vehicles (BEVs) present the most promising option for passenger transportation, offering high efficiency and no exhaust emissions [3]. This has led to a significant increase in new registrations of BEVs in recent years. In 2023, more then half a million BEVs were newly registered in Germany, which corresponds to a share of 18% of all newly registered passenger cars and an increase of 11% compared to 2022 [4,5]. Worldwide, 14 million new vehicles were registered in 2023, an increase of 35% compared to the previous year, resulting in more BEV registrations than ever before [6].

However, these vehicles differ fundamentally from ICEVs in terms of their powertrain. While the majority of the value creation of ICEVs depends on the combustion engine itself, the battery accounts for up to 73% of the powertrain's value creation potential in battery electric vehicles [7]. In order to remain cost-competitive while maintaining the same technical characteristics such as range and acceleration, vehicle manufacturers (also: original equipment manufacturers, OEMs) are increasingly focusing on the further development of battery technologies. However, batteries can vary significantly from one another [8, 9]. They can be made from various cell chemistries. Nickel-rich cell chemistries such as lithium nickel manganese cobalt oxide (NMC) and nickel cobalt aluminum oxide (NCA) currently dominate the vehicle market, whereas the market share of so-called lithium iron phosphate (LFP) cells, which do not require the use of nickel, cobalt or manganese, has risen from 3% to around 30% in the passenger car sector in the last 5 years [10]. Despite notable differences between the various key performance indicators (KPIs) and raw material needs [11].

Against this background, it is increasingly important to understand how future BEV designs will incorporate various components and cell chemistries. This includes not only the development of battery size and vehicle range but also considerations of vehicle costs and the optimal cell chemistries for different vehicle segments. Moreover, understanding these factors is critical to be aware of potential raw material and supply chain dependencies, which play a significant role in the feasibility and sustainability of battery technologies. It is therefore crucial to evaluate the different technologies by their techno-economic feasibility in this highly dynamic market development.

To approach this task with both flexibility and adaptability, we developed a machine learning based OEM agent, calculating the market potential of future BEV energy storage technologies by considering multiple dynamic technical and economic factors. The OEM agent builds on a comprehensive database of technological innovations, bottom-up

* Corresponding author.
E-mail address: samuel.hasselwander@dlr.de (S. Hasselwander).

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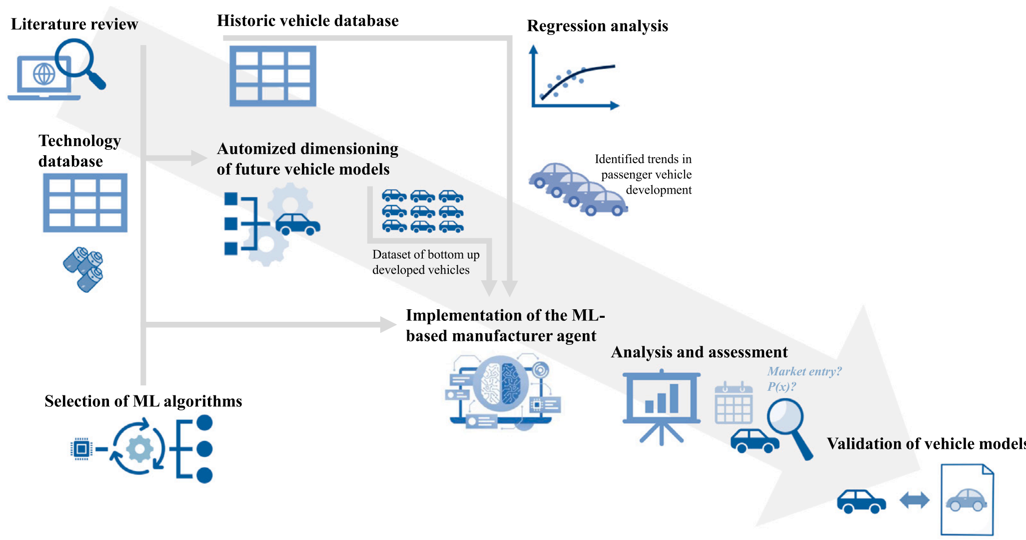


Fig. 1. Schematic diagram of the machine learning-based manufacturer agent model.

vehicle calculations, and historical data from passenger cars, enabling unique insights into emerging market opportunities and challenges. Improving our understanding of the potential future diversification of the BEV market.

2. Trends of battery electric vehicle technologies

Current cell chemistries continue to be optimized in terms of their energy density and production costs. In the case of NMC cells, for example, attempts are being made to reduce the more expensive materials cobalt and manganese by increasing the nickel content, while at the same time increasing the energy density of the cell. In combination with a silicon-doped anode, this could lead to energy densities of up to 1000 Wh/l [11]. In the case of LFP cells, attempts are being made to improve the cell voltage and thus also the energy density at cell level by doping manganese. OEMs are now focusing not just on optimizing individual cell chemistries, but also on how these cells are packaged within the battery system. As the traction battery is assembled from active materials into electrodes, cells, modules, and finally the battery pack, its energy density decreases due to the inclusion of inactive materials like films, housings, control units, and cooling systems. Consequently, current BEVs achieve a volumetric energy density of about 150 to 250 Wh/l at the system level, which is about one-third to one-half of the cell's intrinsic energy density [12]. To address this reduction, OEMs are working on packing cells more densely, increasing the size of modules, or even eliminating modules altogether. This approach, known as cell-to-pack (CtP), involves installing battery cells directly into the system without additional module housings, thereby enhancing the utilization of available space [13]. In such systems, the cells are usually firmly bonded and are then also able to absorb structural loads [14]. Intrinsically safe cell chemistries such as LFP are therefore particularly suitable for the CtP approach. CtP also opens up market potential for less costly sodium-ion (So-Ion) cells, which are initially considered unsuitable for automotive use due to their low energy density, but now sufficient ranges can also be achieved with these lower energy density cells thanks to CtP technology [15–17]. Many international manufacturers and start-ups are actively researching solid state batteries (SSBs), which promise significantly higher energy density by using metallic lithium as the anode [18]. However, due to the high reactivity of lithium, liquid electrolytes cannot be used. Consequently, solid electrolytes made of polymers, ceramics, or hybrid mixtures of both are being used [19]. Despite these advancements, SSBs still face challenges in achieving conductivity, stability, scalability, and cost-effectiveness [20,21]. As a result, they remain in the development stage, with commercialization not expected in the near future.

To stay within the scope of this paper, we have focused solely on the most important parameters related to battery and cell chemistry KPIs. An in-depth techno-economic analysis of these based on an extensive meta-analysis, expert consultations and teardown analyses is presented in [11].

3. Machine learning-based evaluation method

While machine learning models exist for predicting technical parameters such as battery temperature [22], state-of-health [23], or range estimation [24], none currently assess potential future vehicle models, an important task for anticipating technological trends. The OEM agent addresses this by estimating the market entry probability of specific vehicle and battery technologies. This techno-economic assessment combines automatically configured vehicles with various technologies and an agent trained on historical passenger car development, focusing on customer-relevant parameters such as segment, price, range, and weight.

Fig. 1 shows the development process of the OEM agent schematically. The initial dataset of performance parameters for various cell chemistries was compiled into a comprehensive technology database, which has since been further developed and updated throughout this research. Based on the technology database, an automated design of various vehicle configurations is then carried out as an input variable for the ML-based OEM agent, which is explained in more detail in Section 3.1. For training of the neural network, historical vehicle data from the vehicle database of the German Automobile Club (*Allgemeiner Deutscher Automobil-Club e.V.*, ADAC) is used [25]. This dataset, comprising more than 40.000 vehicles, serves as a basis to map the development trends of various vehicle-specific parameters. In the course of data preparation, trends in passenger vehicle development were derived using regression analyses as described in Section 3.2 and passed to the OEM agent as an additional input variable. To optimize the performance of the ML-based OEM agent, three methods were investigated: Neural Networks, K-Nearest Neighbors (KNN), and Binary Classification using Logistic Regression. This comparative evaluation aimed to identify the most effective approach for the agent's decision-making process.

Table 1
Model assumption of the most important key performance indicators (KPI) of cell chemistries of batteries for electric vehicles at cell level.

KPI	Unit	Year	NMC_{811}	LFP	SSB	So-Ion	Source
Gravimetric energy density	Wh/kg	2020	280	185	–	–	[11]
		2025	315	202.5	–	160	
		2030	350	220	400	200	
		2035	350	220	400	200	
		2040	350	220	400	200	
Volumetric energy density	Wh/l	2020	700	430	–	–	[11]
		2025	825	465	–	280	
		2030	950	500	1000	350	
		2035	950	500	1000	350	
		2040	950	500	1000	350	
Gravimetric CtP-Factor	CtMtP[a]	-	0.60	0.60	0.60	0.60	[12]
	CtP[b]		–	0.82	–	0.82	
Volumetric CtP-Factor	CtMtP	-	0.35	0.35	0.35	0.35	[12]
	CtP		–	0.57	–	0.57	
Cell cost	EUR/kWh	2020	107	96	750	357	[11,26]
		2025	89	79	264	126	
		2030	70	60	105	50	
		2035	67	59	96	48	
		2040	64	58	88	46	

[a] CtMtP = Cell-to-Module-to-Pack.
[b] CtP = Cell-to-Pack.

3.1. Automated vehicle configuration based on technology database

A comprehensive technology database was established as the foundation for the automated design and configuration of possible future passenger vehicles, serving as one main input for the OEM agent. The database is organized in a hierarchical structure, comprising four main dimensions that categorize data according to the technological components of battery, power electronics, electric motor, and general assumptions about the vehicle, which can be flexibly configured in three different segments: small, medium and large. Each dataset contains detailed information on technical or physical quantities, including value, unit, data source, and author. This structured approach enables efficient tracing of information and validation of its accuracy. Utilizing object-oriented data management principles, a class-based framework was developed to represent each technology component, promoting clear structuring, modularity, re-usability, and extensibility. Below is a list of the technical information that has been assumed regarding the different battery technologies, electric motors and the vehicle itself.

The database includes four cell chemistries: lithium nickel manganese cobalt oxide (NMC) with a 80% Ni, 10% Mn, and 10% Co composition; lithium iron phosphate (LFP); solid-state batteries (SSB); and sodium-ion battery cells. The model assumptions from [11] are used regarding the values of gravimetric and volumetric energy density for the years 2020 and 2030. The values for 2025 are determined using linear interpolation. A conservative assumption is made for the years after 2030, meaning that the improvement in energy density stagnates and retains its value. Table 1 shows the assumed KPIs as used for the vehicle configurations.

The gravimetric and volumetric cell-to-pack (CtP) factors, in other words the ratio of usable energy at cell level to overall usable energy of the traction battery, are based on the average value across various teardown analyses of available vehicle models done by A2Mac1 [12]. In addition to the conventional cell-to-module-to-pack (CtMtP) technology, we also considered the direct integration of the battery cells into the pack. This so called cell-to-pack technology results in a higher CtP factor or degree of utilization of the energy density at system level due to the lower number of inactive materials. Our cost assumptions for battery cells are based on an own techno-economic analysis, incorporating insights from literature reviews, expert input, and teardown assessments [11]. For the ramp-up and the period in between the base years, we have relied on the cost trajectories developed by BloombergNEF [27], which describe the expected cost development of new battery chemistries. A more detailed breakdown of these projections can be found in [26].

As the focus of this paper is on the development of energy storage technologies, the technical data of the three different electric motors considered: permanent magnet synchronous motor (PMSM); current excited synchronous motor (CESM); and induction or asynchronous motor (ASM) are listed in Table A.2 in the appendix for reasons of space.

The same applies to the general vehicle parameters which are listed in Table A.3 in the appendix. We considered vehicles in the small segment (e.g. Renault Zoe), medium segment (VW ID.3) and large segment (Mercedes EQS). Based on the model assumptions outlined in [11], the technical specifications in Table A.3 were derived. Assuming continuous advancements in efficiency, including e-motor transmission, power electronics, and coefficient of friction, we accounted for improvements across future vehicle generations. For intermediate years, data was extrapolated via linear interpolation.

In order to be able to evaluate the entire spectrum of future vehicle concepts with the specially developed OEM agent described in this paper, the variety of possible models must first be generated and analyzed. This is done by linking all possible combinations of the components contained in the technology database and thus compiling new unique vehicle models for the various support years as displayed in Fig. 2.

In addition to the battery type, e.g. NMC or LFP, the CtP technology is also taken into account in the vehicle configuration. Based on [26], it is assumed that this is primarily used for intrinsically safe cell chemistries such as LFP or So-Ion. As described in [11], the battery capacity results from the available battery volume of the corresponding vehicle segment. In order to reflect the reality of the vehicle market, in addition to the maximum possible battery capacity, vehicles are also configured that have a slightly reduced capacity and therefore a shorter range. Resulting in standard range (SR) and long range (LR) vehicle models. The latter fully utilize the available installation space for the use of batteries. Furthermore, up to two different electric motors can be installed per vehicle. The modular design of the OEM agent enables easy integration of new components, so different power electronics will be included in the next iteration.

The model then automatically calculates the energy consumption and vehicle range in the worldwide harmonized light vehicles test procedure (WLTP) for each vehicle configuration, as described in [11]. A bottom-up cost calculation is performed alongside the technological evaluation to determine vehicle costs based on segment, chemistry and powertrain technology.

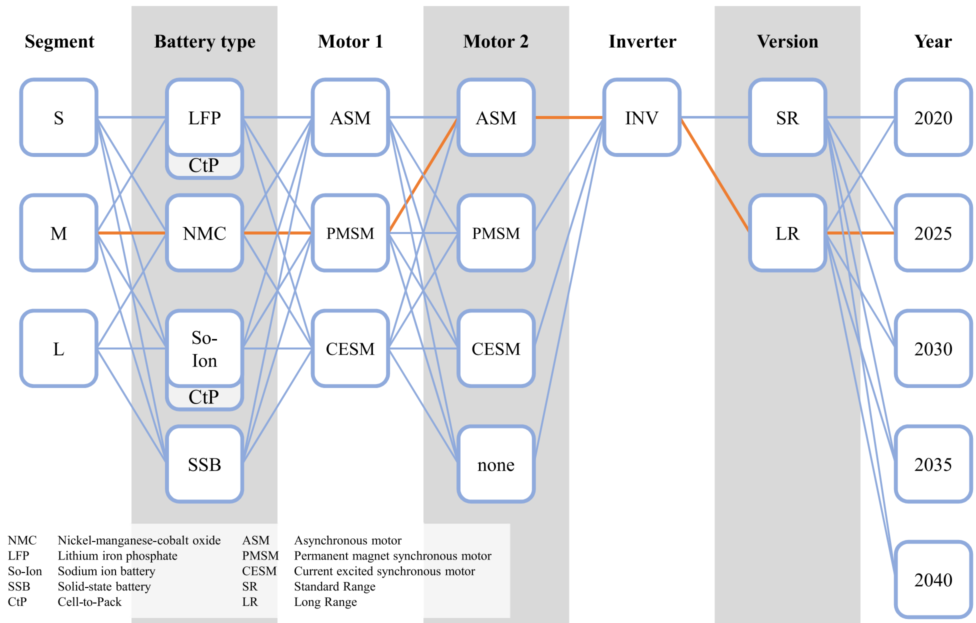


Fig. 2. Summary of all possible combinations of the technology components currently included in the database. The orange example shows a 2025 medium-size BEV with NMC cells, one PMSM, one ASM, and a long-range battery. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Implementation of manufacturer agent

The aim of the developed neural network is to calculate the probability of the market entry year of new vehicles based on a wide range of input data. This data includes the bottom-up calculated specific characteristics of the vehicles such as battery capacity, vehicle weight, WLTP range and vehicle price. However, it is important to emphasize that the network can be flexibly configured to obtain different target values depending on the specific question, or to use even more specific input data. For example, the same model structure and approach can be used to assign possible future vehicle models to different manufacturer groups.

The implemented neural network consists of a multilayer feed-forward neural network implemented using the Keras library with TensorFlow as backend. The architecture includes several dense layers, the number and the size of which were determined based on preliminary experiments to optimize model performance. The input layer takes in the pre-processed vehicle data, while the output layer provides the probability for each possible year of market entry. The model consists of several layers: an input layer which consists of 20 neurons and uses a linear activation function, an hidden layer which also consists of 20 neurons and uses a linear activation function and an output layer which uses a sigmoidal activation function to calculate the probabilities for different years.

The model utilizes the Adam optimizer and binary cross entropy as its loss function. In order to be able to use the neural network as a classifier, a training data set is generated, based on the ADAC vehicle database [25], reflecting the expected trends in various vehicle parameters for future years. This was achieved through regression analysis of historical vehicle data, taking into account both technical and economic factors, such as cost developments. The input parameters were categorized into two types: categorical (e.g., used cell chemistry) and numerical (e.g., vehicle range). We focused on the latter type, as they allow for temporal correlations, and selected the following key metrics based on an extensive parameter analysis: battery capacity, vehicle range, weight and list price.

While numerical values can be extrapolated using regression methods, simply summarizing all historical vehicle data is insufficient for predicting trends in vehicle technology variables. To effectively analyze these trends, it is necessary to divide the data into distinct segments. For this purpose, the historical vehicle data was categorized into the three segments: small, medium and large. By doing so, we can isolate specific trends within each category that might otherwise be obscured by the diversity of the entire dataset.

The ADAC dataset contains data of over 42,000 vehicle models as of July 2024. As we are focusing purely on BEVs in this work, vehicles with non-battery electric powertrains and other irrelevant or incorrect data sets were removed (cf. B). Fig. 3 shows the average yearly key metrics of the almost 500 BEV models analyzed. The number above each data point represents the count of available models being averaged in that specific year.

It becomes clear that there is an upward trend for almost all the parameters under consideration. For example, the average battery capacity increases from 65 kWh in 2020 to 75 kWh for newly available medium-size vehicle models in 2024, while the vehicle range improves from around 410 km to nearly 500 km over the period shown. However, due to physical constraints such as limited installation space, linear growth is unlikely for these characteristics. To better capture this development, we use an exponential trend function, enhanced by calculated vehicle models derived from literature, as indicated by the data points for the year 2030, to accurately represent physical limitations. This extension enables a more realistic prediction of model development based on current research results.

The OEM agent's training data is generated using the shown trend curves. In order to increase the number of vehicles available for training the neural network, data augmentation was carried out. This step is essential for enhancing the dataset's variability and enabling the model to better withstand novel, unseen data. All parameters identified as relevant (namely: battery capacity, vehicle range, weight and list price) are defined as input variables x, with the exception of the model year, as the latter serves as the target variable y. To optimize the performance of the neural network, the input variables are then standardized ensuring that all input variables have a similar scale.

4. Analysis and evaluation of developed future vehicle models

4.1. Testing of the manufacturer agent

The input data described above is split into training and test data to evaluate the model, with a typical ratio of 80% to 20%. For training,

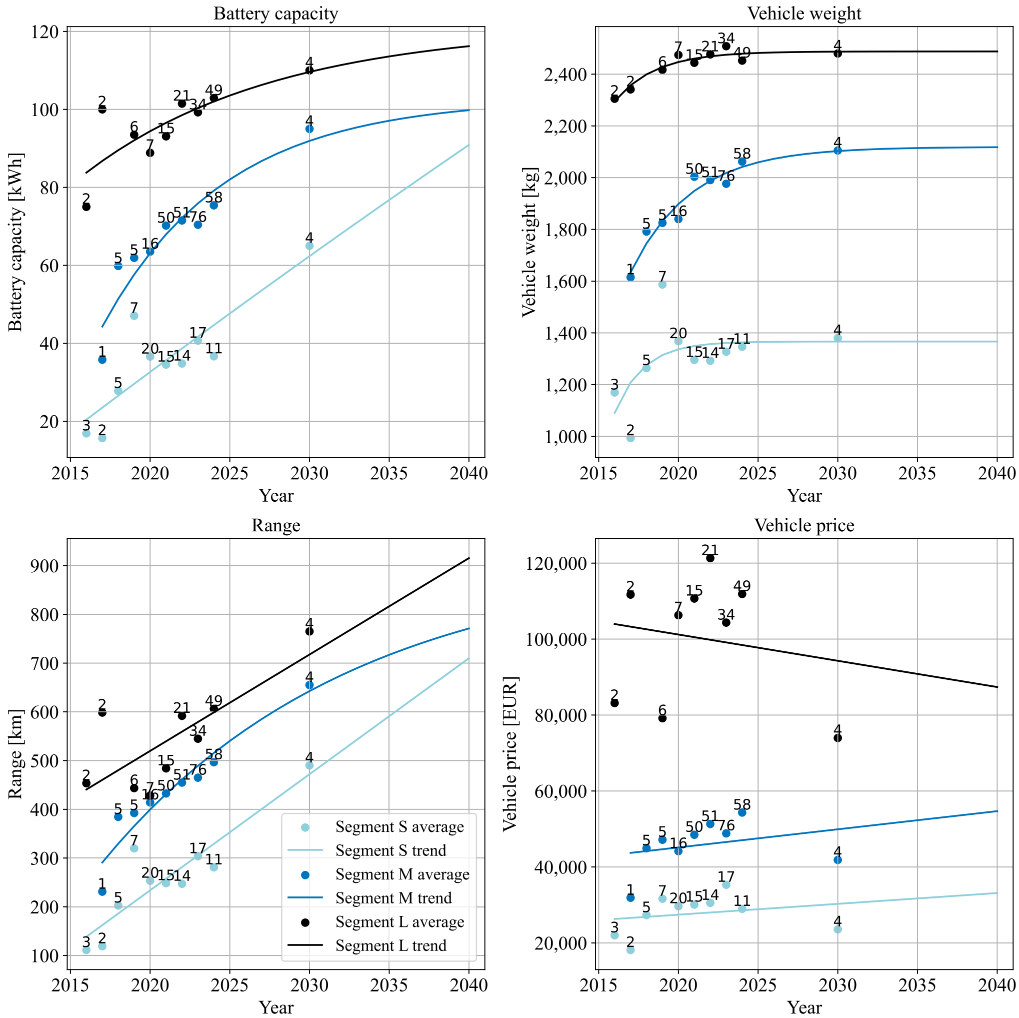


Fig. 3. Average yearly key metrics of battery electric vehicle models available in Germany as listed in [25] segmented by vehicle size. The number above each data point represents the count of available models being averaged in that specific year. Projected trends are also shown, using regression analysis and calculated vehicle models derived from literature to accurately represent physical limitations.

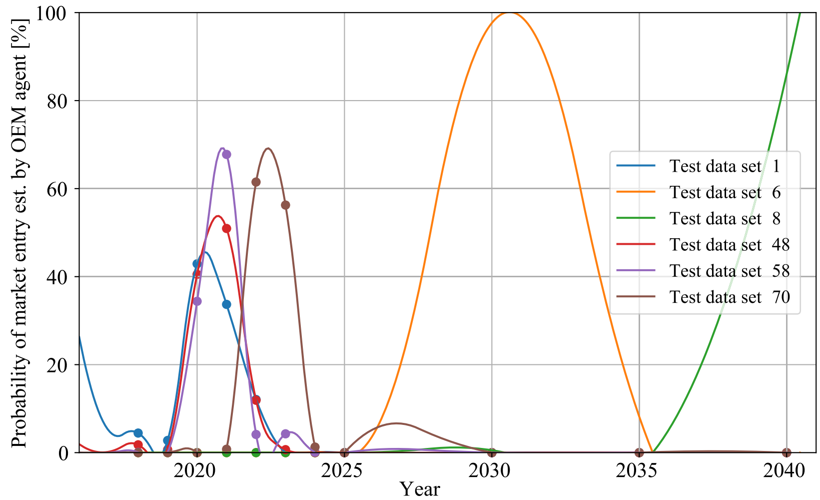
the cross entropy is used as a loss function to minimize the deviation between the predicted and actual values. The Adam optimizer of the Keras library, a variant of the stochastic gradient descent method, was selected due to its efficient and fast convergence characteristics. The training comprises 200 epochs. After training, the model is evaluated with the test dataset to measure performance and generalization ability. The model evaluation is based on the calculation of accuracy, which is typically defined as the proportion of test data samples correctly classified relative to the total number processed. This metric effectively quantifies the model's ability to accurately predict classification for novel, unseen data.

In the training data set, the identified trends in passenger vehicle development based on the ADAC database is combined with the bottom up developed future vehicles using the component database as described in Section 3.1. With this dataset, the model achieves a classification accuracy of 64%. This means that almost two thirds of the data records are assigned to the correct year of market entry by the highest probability. Fig. 4(a) shows an excerpt from the example dataset illustrating the probability of different market entry years estimated by the OEM agent for a set of test data during training. This prediction was made using the combined ADAC database and the bottom up calculated future vehicle dataset, which were configured based on the component database, as an input.

It turns out that the existing models in particular are correctly classified as currently available models. For the two possible future vehicle models shown, market entry years 2030 and 2040 are identified as the most promising market entry years. In this case, this also corresponds to the years from which the KPIs for configuring the models were taken. The model can therefore reliably assign most current vehicles to the market entry year. However, the overall accuracy of the model is affected if, as shown in test data set 1, the actual year of market entry of the e.Go Life is misclassified by one year compared to the correct value (i.e., 2020 instead of 2019). The primary reason for this decreased accuracy lies in the greater similarity between the currently existing models, which makes it harder for the model to distinguish them. In contrast, the bottom-up generated vehicles exhibit more significant differences in their KPIs, largely due to the longer time period, making them easier to differentiate.

4.2. Evaluation of market relevance and trends of future vehicle technologies

This chapter summarizes the evaluation results of the OEM agent with regard to the automatized bottom-up configured future vehicles. It looks at the market potential of different cell chemistries in the various vehicle segments and also shows how different manufacturer clusters could differ in terms of future battery technologies. The model uses the weightings it has generated during training to make predictions for the vehicle data. These results are assignment probabilities of the classes considered on the basis of the given input data as described in



(a)

Variable	Unit	Test data set 1	58	2	42	6	70
Segment		S	M	M	M	S	L
OEM		e.GO	Skoda	Citroen	Mercedes	-	-
Model		Life	Enyaq	C4	EQA	-	-
Real market entry		2019	2021	2023	2024	-	-
Battery capacity	kWh	23	55	82	76	66	150
Vehicle weight	kg	1,231	1,937	2,230	2,045	1,273	2,545
Range	km	89	355	545	560	491	1,100
Price	EUR	24,650	34,600	53,400	52,205	28,488	89,574
Market entry est. by OEM agent		*2020*	*2021*	*2023*	*2024*	*2030*	*2040*

(b)

Fig. 4. (a) Probability of market entry estimated by the OEM agent for exemplary test data during training with the combined identified trends in passenger vehicle development based on the ADAC database and the bottom up developed future vehicles using the component database. The intermediate values are interpolated to obtain an approximately continuous probability distribution. (b) Associated excerpt of the test data during the training featuring real information about the vehicle models and the estimated market entry year specified by the OEM agent.

Section 3.2. To evaluate market relevance, the model year is chosen as the key identifier. The years 2020 to 2040 are considered in 5-year intervals.

Fig. 5 shows the estimated market relevance of different example vehicle configurations in the small segment for future battery technologies and model years classified by the OEM agent. The underlying vehicle information such as battery capacity, energy consumption, range, and vehicle price for the different years is shown in Appendix C, Table C.4. The vehicles shown correspond to the average of all vehicles assigned to that specific criterion. These criteria include year, battery chemistry, vehicle version (short range and long range) and number of electric motors. In order not to exceed the number of vehicles to be presented, only vehicles with one motor are included in the analysis for the small vehicle segment based on an analysis of average electric motor count of all the currently available vehicle models in this segment.

In the small segment as shown in Fig. 5, vehicles with LFP and LFP-CtP batteries, as well as So-Ion batteries, are expected to have a high market potential in the near future. This is mainly caused by their low cost and currently also still low range of vehicles in the small segment. However, the relevance of the So-Ion battery is declining, while LFP (specially the higher range CtP version) will still be one of the relevant cell chemistries. NMC cell chemistry will remain of greater importance from today until 2030. Although the market relevance decreases until 2040, which is mainly due to the increasing technology readiness of SSBs, NMC cells are still expected in the small segment. From 2030, the solid-state battery is taken into account, which will become increasingly important in the years 2030 to 2040 due to the assumed cost decrease (cf. Table 1), especially in the long-range version.

A general trend observed in the small vehicle segment shows that all cell chemistries are becoming less relevant over time. This decline could be attributed to overly optimistic model assumptions, as the regression curves predict a battery capacity of around 80 kWh and a range of 700 km by 2040 for vehicles in that segment. The possibility that advances in battery technology do not materialize as predicted or take longer than expected may lead to a reduction in the market relevance of the respective cell chemistries.

Across all segments (cf. Appendix C), LFP batteries show a high market relevance initially, but decline over time. However, LFP with CtP technology extends the battery technology's lifespan and keeps it relevant for longer due do the possible higher ranges. NMC remains an essential cell chemistry in every segment, maintaining a consistent level of relevance compared to other technologies throughout the years. Solid-state batteries gain significance from 2030 onwards and increase in market relevance up to 2040, particularly for long-range vehicle versions.

While market relevance is a critical factor influencing the potential entry of new vehicle models, other "soft" considerations such as supplier relationships, standardized battery component sizes, and production facility configurations also play significant roles. One key benefit of utilizing our ML-based OEM agent is that the target parameters can be variably adjusted. In the following analysis, we adapt the agent's configuration to predict the manufacturer group, rather than focusing solely on potential market entry years.

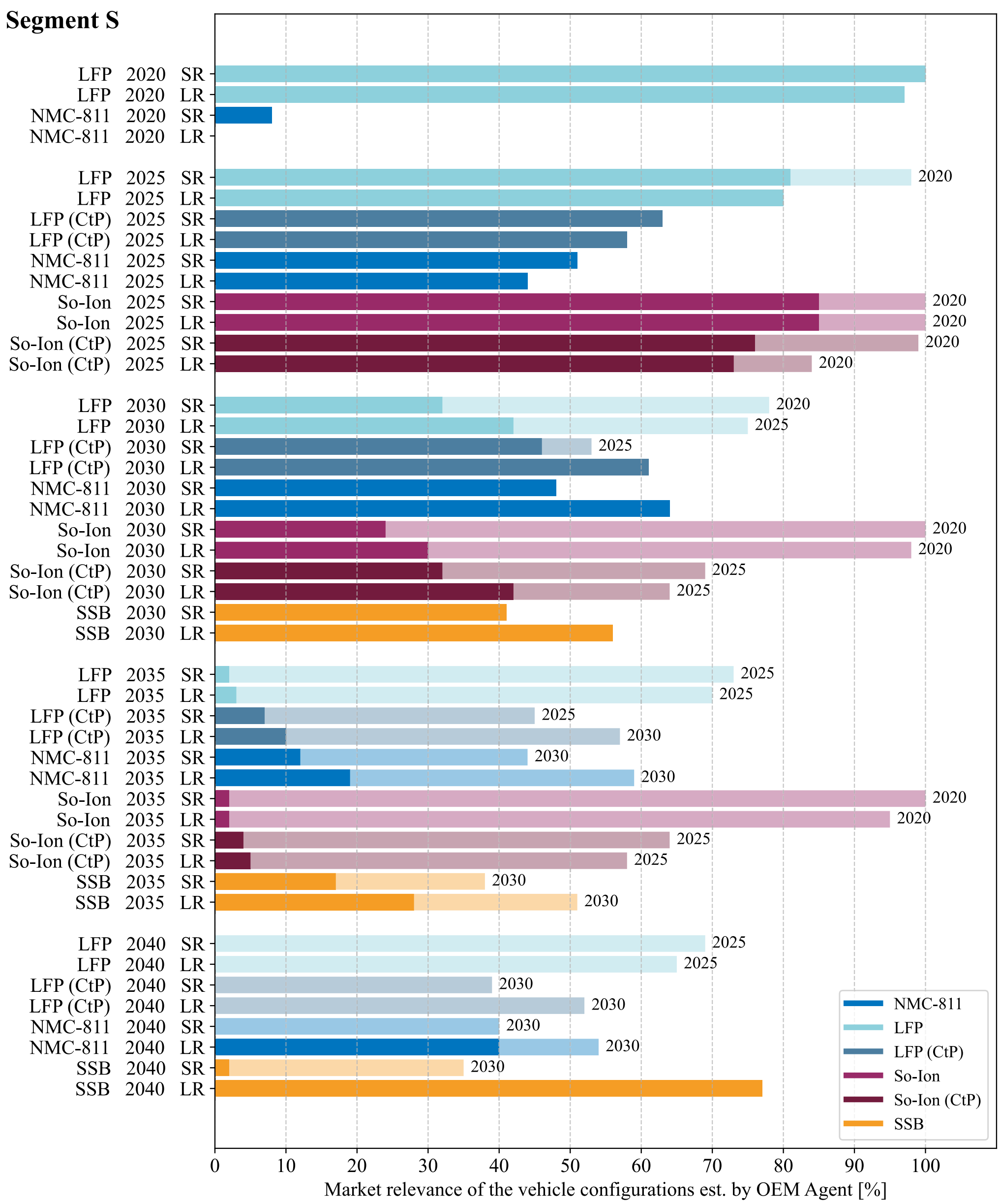


Fig. 5. Market relevance of different example vehicle configurations for future battery technologies and model years in the small segment based on estimations of the OEM agent. The transparent bars illustrate the probability of models that are more likely to enter the market in an earlier year than in the year in which they are technically feasible.

The classification framework comprises four distinct categories, which were identified through a K-means cluster analysis at the outset. The categorization was based on two key criteria: the number of new vehicles per year, average vehicle prices. The identified categories are:

- Volume and low-cost manufacturers (e.g. Dacia, Peugeot, Citroen)
- Premium and niche manufacturers (e.g. Porsche, Polestar)
- Premium manufacturers with high volumes (e.g. Audi, BMW)
- Volume manufacturers with moderate prices (e.g. VW)
- Luxury manufacturers (e.g. Ferrari)

Fig. 6 indicates the estimated market relevance of the considered battery technologies with regard to the manufacturer clusters (a) premium and niche manufacturers and (b) volume and low-cost manufacturers. The height of each bar represents the average assignment probability of all bottom-up generated vehicles from 2035 and 2040 for the respective OEM cluster.

It can be seen that vehicles with So-Ion and LFP cell chemistry are increasingly classified with volume and low-cost manufacturers. This is plausible because these are the cheapest cell chemistries considered in the analysis. Vehicles with more expensive and higher performance cell chemistries such as NMC or SSBs are more likely to be allocated to premium and niche manufacturers. That is because these manufacturers are willing to pay higher prices for better performance, range and innovation in order to increase the competitiveness of their vehicles.

5. Discussion of methodology and results

The market relevance analysis reveals a notable alignment between current manufacturer strategies and the trends observed in vehicle concepts. A common approach among manufacturers is to focus on specific cell chemistries based on the vehicle segment, with LFP and So-Ion batteries suitable for smaller vehicles, while NMC being used in larger vehicles [28–31].

The analysis also highlights the growing importance of solid-state batteries across all segments, particularly for premium and long -distance vehicles. These batteries promise higher energy densities and

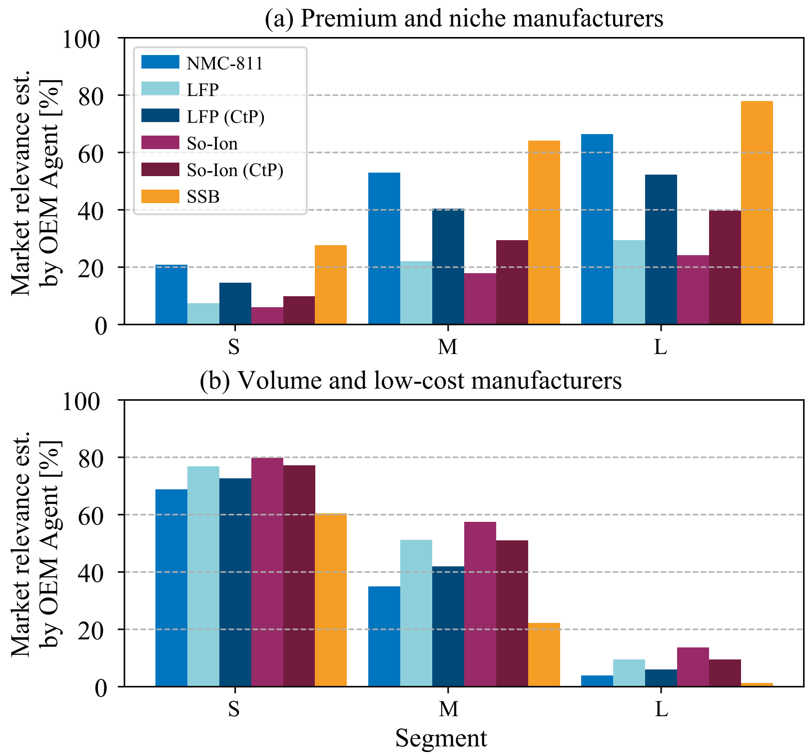


Fig. 6. Market relevance of future battery technologies for different manufacturer clusters based on estimations of the OEM agent.

longer ranges, making them an attractive option for manufacturers looking to improve their offering to meet customers' demands for longer vehicle ranges [18].

Furthermore, the model results suggest that vehicle prices will decrease due to cost reductions, partly driven by the use of cheaper battery cells like So-Ion or the adoption of cell-to-pack technology [32,33]. This trend is also reflected in the manufacturer's strategies to further reduce costs, increase efficiency and at the same time maximize the vehicle range [34], which is consistent with the allocation probabilities determined in the analysis.

While the OEM agent model has shown promising results in aligning with current technology trends and manufacturer strategies, it is not without its limitations. One major limitation is the availability of data, which is currently limited to a relatively short period of time (including BEV models from 2016 to 2024 only). This makes it challenging to provide reliable long-term predictions and assessments of market relevance. Furthermore, being at an early stage in the development of BEVs means that long-term forecasts are inherently uncertain and prone to being overtaken by technological leaps and innovations. The conservative assumption taken in the analysis assuming constant energy densities from 2030 onwards is a reflection of this uncertainty, but it also implies that possible game-changing advancements may not be accounted for in the assessment. Finally, the exponential saturation function used in the regression analysis to simulate physical limits may not accurately capture the potential impact of new innovations on market trends. This means that the OEM agent model's predictions may be overly cautious and do not fully account for the possibilities of future breakthroughs and paradigm shifts in the industry.

While the OEM agent allows statements to be made about the potential market entry of new vehicle models, several other "soft" factors are crucial in determining the actual development of these vehicles. In particular, supplier relationships, standardized sizes of battery components, and configurations of production facilities all play important roles in this process. However, due to a lack of data availability, these factors have not yet been incorporated as input parameters by the OEM agent.

This is where the main benefit of the developed machine learning based manufacturer agent comes into play: its flexibility and adaptability. The model can be easily expanded or modified as needed, using newly available data, without requiring significant changes to the underlying code. That flexibility is made possible by an external database management system that allows new technologies to be incorporated without requiring changes to the underlying code. Additionally, the object-oriented data structure enables a seamless integration of new components and technologies into the existing model, automatically taking them into account in the vehicle design. This makes it possible to quickly develop and deploy a tailored model for new problems or scenarios, using the same underlying framework.

6. Conclusion

A machine learning-based manufacturer agent model has been successfully developed and applied to analyze and forecast market trends in the automotive sector. By integrating a comprehensive database of technological innovations, bottom-up calculated vehicles and historical data from passenger cars, the neural network was trained to evaluate the potential of various possible future vehicle models, providing insights into emerging market opportunities and challenges.

The analysis reveals significant potential for battery chemistry diversification within the market of battery electric vehicles. Showing an increasing market potential for LFP and So-Ion vehicle models featuring cell-to-pack technology in the small vehicle segment. As future vehicles demand greater ranges, solid-state batteries are likely to enter the market alongside existing high-energy-density NMC cells, provided that technological readiness and cost reductions are achieved. In the near future, however, NMC cells are expected to remain the most important cell chemistry and may retain a competitive advantage over the other technologies due to their currently high usage.

To date, discussion and research on battery electric vehicles has primarily centered on increasing range and reducing costs. This paper is no exception, but it also lays the groundwork for future investigations that can expand the scope to other essential factors. With the aid of the OEM agent model, it becomes possible to incorporate other critical factors into future discussions such as the CO_2-footprint of the vehicle, provided that relevant data becomes available. This future expansion will enable an even deeper understanding of market trends and opportunities.

CRediT authorship contribution statement

Samuel Hasselwander: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Julian Rettich:** Writing – review & editing, Visualization, Methodology, Formal analysis, Data curation. **Stephan Schmid:** Writing – review & editing, Supervision. **Tjark Siefkes:** Writing – review & editing, Supervision.

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.

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Appendix A. Technology database

Table A.2 shows the technical data of the three different electric motors considered: permanent magnet synchronous motor (PMSM); current excited synchronous motor (CESM); and induction or asynchronous motor (ASM) as specified in [11].

Table A.3 shows the technical data of the three different vehicle segments: small (e.g. Renault Zoe); medium (VW ID.3); and large (Mercedes EQS) as specified in [11].

Appendix B. ADAC dataset

The ADAC vehicle database [25] serves as the foundation for training the OEM agent, with our specific version incorporating data of over 42,000 vehicle models as of July 2024. The database contains all vehicle models that have been available in Germany since 2016 as well as their technical specifications, component details and information on vehicle costs. The original database can only be made available by licensing directly through the ADAC.

To ensure the quality of the data, irrelevant or incorrect data sets were removed. This was done using defined filter criteria, which ensured that only valid data relevant for the analysis was included. Fig. B.7 shows the technical parameters of the filtered final selection of almost 500 battery electric vehicle models divided into the segments S, M and L.

Table A.2
Key performance indicators (KPIs) of considered electric motors [11].

KPI	Unit	PMSM	CESM	ASM
Motor efficiency	–	0.95	0.93	0.90
Component cost	EUR	700	590	570

Table A.3
Model assumption of the technical specifications of the S, M and L vehicle segments [11].

Parameter	Year	Unit	S-Segment	M-Segment	L-Segment
Vehicle mass[a]		kg	1251	1440	1798
Drag coefficient		–	0.33	0.27	0.2
Frontal area		m^2	2.27	2.36	2.51
Battery volume		l	270	340	420
Rolling resistance coefficient	2020	–	0.0090	0.0090	0.0090
	2025	–	0.0087	0.0087	0.0087
	2030	–	0.0083	0.0083	0.0083
	2035	–	0.0080	0.0080	0.0080
	2040	–	0.0077	0.0077	0.0077
Battery charging efficiency (AC)	2020	–	0.95	0.95	0.95
	2025	–	0.96	0.96	0.96
	2030	–	0.97	0.97	0.97
	2035	–	0.98	0.98	0.98
	2040	–	0.99	0.99	0.99
Battery discharging efficiency (AC)	2020	–	0.95	0.95	0.95
	2025	–	0.96	0.96	0.96
	2030	–	0.97	0.97	0.97
	2035	–	0.98	0.98	0.98
	2040	–	0.99	0.99	0.99
Efficiency of power electronics	2020	–	0.95	0.95	0.95
	2025	–	0.96	0.96	0.96
	2030	–	0.97	0.97	0.97
	2035	–	0.98	0.98	0.98
	2040	–	0.99	0.99	0.99
Gearbox efficiency	2020	–	0.9800	0.9800	0.9800
	2025	–	0.9825	0.9825	0.9825
	2030	–	0.9850	0.9850	0.9850
	2035	–	0.9875	0.9875	0.9875
	2040	–	0.9900	0.9900	0.9900

[a] Without battery.

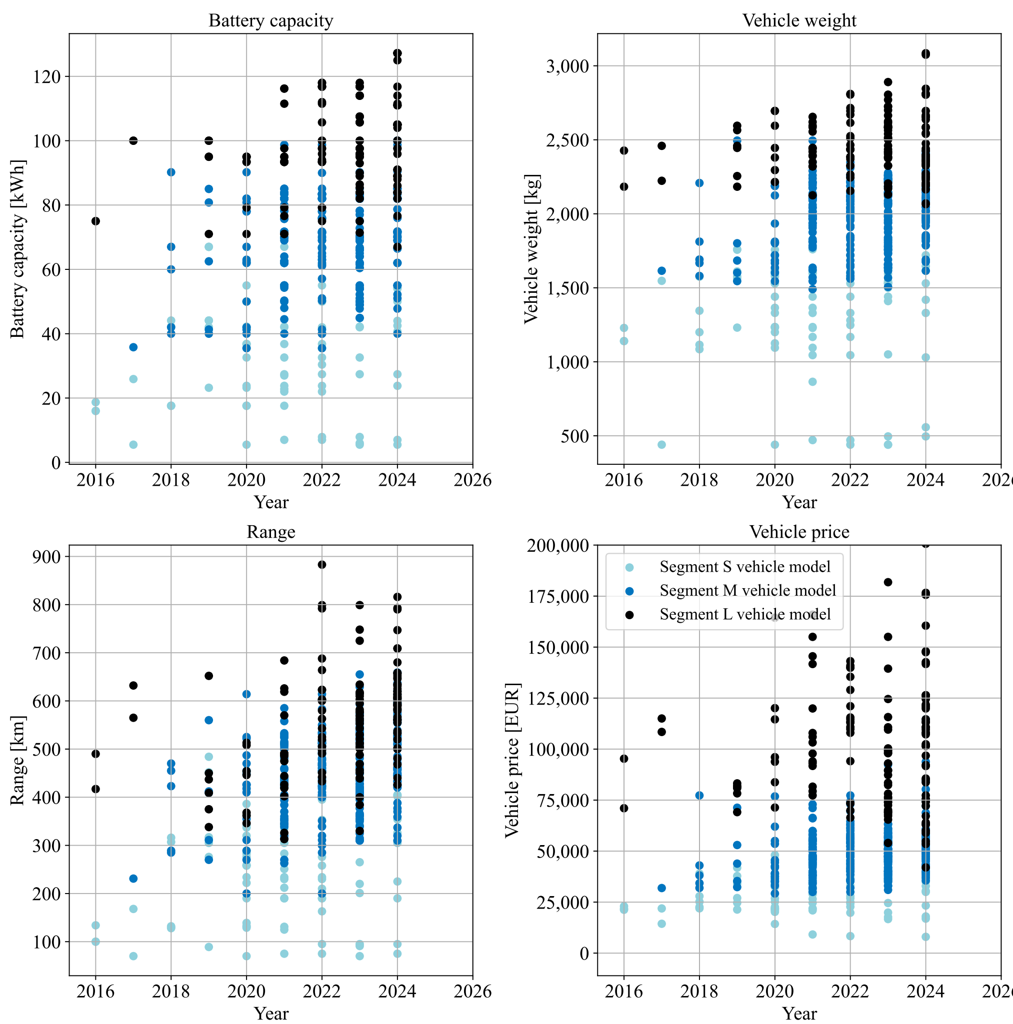

Fig. B.7. Key metrics of the filtered final selection of battery electric passenger car models available in Germany from 2016 to 2024 according to [25], segmented by vehicle size.

Table C.4
Technical specifications and market relevance as estimated by the OEM agent (P%) of the example vehicle configurations in the small segment as displayed in Fig. 5.

Segm.	Year	Battery chemistry	Vehicle version	Capacity [kWh]	Consumption [kWh/100 km]	Range [km]	Price [EUR]	P%
S	2020	LFP	SR[a]	33	15.3	217	24.335	100
		LFP	LR[b]	41	15.6	261	26.248	100
		NMC-811	SR	54	15.4	350	31.109	36
		NMC-811	LR	66	15.7	421	34.579	1
	2025	LFP	SR	36	14.5	247	23.419	88
		LFP	LR	44	14.8	298	25.122	90
		LFP (CtP)	SR	58	14.7	395	28.072	79
		LFP (CtP)	LR	72	15.1	475	30.844	81
		NMC-811	SR	63	14.7	433	30.811	68
		NMC-811	LR	78	15.0	520	34.214	68
		So-Ion	SR	22	14.2	152	23.126	87
		So-Ion	LR	26	14.4	184	24.761	88
		So-Ion (CtP)	SR	35	14.4	244	27.594	79
		So-Ion (CtP)	LR	43	14.6	295	30.257	79
	2030	LFP	SR	38	13.7	280	22.063	49
		LFP	LR	47	14.0	338	23.453	64
		LFP (CtP)	SR	63	14.0	449	25.862	69
		LFP (CtP)	LR	77	14.3	540	28.126	84
		NMC-811	SR	73	14.0	524	29.416	69
		NMC-811	LR	90	14.3	630	32.498	84
		So-Ion	SR	27	13.5	200	19.544	35
		So-Ion	LR	33	13.7	242	20.355	46
		So-Ion (CtP)	SR	44	13.6	322	21.760	50
		So-Ion (CtP)	LR	54	13.9	389	23.081	66
		SSB	SR	77	13.8	556	37.173	46
		SSB	LR	94	14.2	669	42.038	63
	2035	LFP	SR	38	13.0	296	21.962	3
		LFP	LR	47	13.2	357	23.329	6
		LFP (CtP)	SR	63	13.2	475	25.698	15
		LFP (CtP)	LR	77	13.5	571	27.924	29
		NMC-811	SR	73	13.2	554	28.842	25
		NMC-811	LR	90	13.5	666	31.791	47
		So-Ion	SR	27	12.8	211	19.403	2
		So-Ion	LR	33	12.9	256	20.182	2
		So-Ion (CtP)	SR	44	12.9	340	21.531	5
		So-Ion (CtP)	LR	54	13.1	411	22.798	9
		SSB	SR	77	13.1	587	35.360	27
		SSB	LR	94	13.4	708	39.808	51
	2040	LFP	SR	38	12.3	314	21.861	0
		LFP	LR	47	12.5	379	23.205	0
		LFP (CtP)	SR	63	12.5	503	25.534	0
		LFP (CtP)	LR	77	12.7	606	27.722	0
		NMC-811	SR	73	12.5	587	28.268	0
		NMC-811	LR	90	12.7	707	31.085	23
		SSB	SR	77	12.4	622	33.748	0
		SSB	LR	94	12.6	751	37.826	70

[a] Standard range.
[b] Long range.

Appendix C. Model outputs

The values presented in the tables and figures below show the technical specifications and estimated market relevance of different example vehicle configurations in the small, medium and large segment for future battery technologies and model years classified by the OEM agent. The tables and figures below represent the average of all bottom-up configured vehicles grouped by specific criteria, including year, battery chemistry, vehicle version (standard range or long range), and number of electric motors.

To maintain a manageable number of data points, the analysis includes: single-motor vehicles in the small segment; standard-range vehicles with one motor and long-range vehicles with two motors in the medium segment; and all large vehicles with two electric motors. This selection is based on an analysis of average electric motor count by segment, which found that the small segment predominantly features single-motor vehicles, the large segment two-motor vehicles, and the medium segment exhibits a trend towards two-motor vehicles, although the current average across all medium vehicle models considered is at around 1.4 electric motors.

Fig. 5 provides the underlying vehicle data for the configurations shown in Fig. 5, which estimates the future market relevance of selected small-segment BEV configurations across battery technologies and model years, as classified by the OEM agent. The table includes average values for battery capacity, energy consumption, range, and vehicle price for each configuration. These configurations are defined by year, battery chemistry, version (short or long range), and number of electric motors. To keep the analysis manageable and based on current market trends, only single-motor vehicles are considered, reflecting the typical motor count in this segment.

C.1. Model results of the medium vehicle segment

Fig. C.8 presents the estimated market relevance of selected example configurations for medium-segment BEVs, differentiated by battery technology, model year and range option, as classified by the OEM

Table C.5
Technical specifications and market relevance as est. by the OEM agent (P%) of the example vehicle configurations in the medium segment as displayed in Fig. C.8.

Segm.	Year	Battery chemistry	Vehicle version	Capacity [kWh]	Consumption [kWh/100 km]	Range [km]	Price [EUR]	P%
M	2020	LFP	SR[a]	42	15.4	270	38.446	100
		LFP	LR[b]	51	16.5	311	42.043	100
		NMC-811	SR	68	15.6	435	46.976	78
		NMC-811	LR	83	16.6	501	52.534	35
	2025	LFP	SR	45	14.6	309	37.293	45
		LFP	LR	55	15.5	357	40.624	49
		LFP (CtP)	SR	73	14.9	492	43.151	22
		LFP (CtP)	LR	90	15.9	567	47.830	22
		NMC-811	SR	80	14.8	539	46.602	17
		NMC-811	LR	98	15.8	621	52.074	16
		So-Ion	SR	27	14.2	191	36.924	62
		So-Ion	LR	33	15.0	222	40.170	67
		So-Ion (CtP)	SR	44	14.4	306	42.550	46
		So-Ion (CtP)	LR	54	15.3	354	47.091	50
	2030	LFP	SR	48	13.8	352	35.584	15
		LFP	LR	60	14.6	408	38.523	17
		LFP (CtP)	SR	79	14.0	562	40.369	20
		LFP (CtP)	LR	97	15.0	648	44.407	24
		NMC-811	SR	92	14.0	656	44.845	21
		NMC-811	LR	113	15.0	756	49.913	26
		So-Ion	SR	34	13.4	253	32.413	14
		So-Ion	LR	42	14.2	294	34.622	15
		So-Ion (CtP)	SR	55	13.6	405	35.204	16
		So-Ion (CtP)	LR	68	14.4	470	38.055	19
		SSB	SR	97	13.9	697	54.612	20
		SSB	LR	119	14.8	805	61.927	25
	2035	LFP	SR	48	12.9	375	35.458	5
		LFP	LR	60	13.7	434	38.367	5
		LFP (CtP)	SR	79	13.2	598	40.162	19
		LFP (CtP)	LR	97	14.0	691	44.153	26
		NMC-811	SR	92	13.2	698	44.122	31
		NMC-811	LR	113	14.0	806	49.023	44
		So-Ion	SR	34	12.6	269	32.236	3
		So-Ion	LR	42	13.3	313	34.404	3
		So-Ion (CtP)	SR	55	12.8	431	34.915	7
		So-Ion (CtP)	LR	68	13.6	500	37.699	9
		SSB	SR	97	13.1	742	52.329	34
		SSB	LR	119	13.9	858	59.118	47
	2040	LFP	SR	48	12.1	400	35.331	0
		LFP	LR	60	12.8	464	38.211	0
		LFP (CtP)	SR	79	12.4	639	39.955	31
		LFP (CtP)	LR	97	13.1	740	43.899	58
		NMC-811	SR	92	12.4	745	43.399	92
		NMC-811	LR	113	13.1	863	48.134	99
		SSB	SR	97	12.2	791	50.299	99
		SSB	LR	119	13.0	918	56.622	100

[a] Standard range.
[b] Long range.

agent. The corresponding vehicle data such as average battery capacity, energy consumption, range, and price can be found in Table C.5.

In the medium segment, LFP batteries show high initial market relevance but decline over time. However, the introduction of LFP with Cell-to-Pack technology extends their competitiveness by enabling higher ranges, thus maintaining their relevance longer. NMC remains a core cell chemistry, showing stable market relevance throughout the years. Solid-state batteries begin to gain significance from 2030 onward, with growing relevance through 2040—particularly in long-range vehicle configurations.

C.2. Model results of the large vehicle segment

Fig. C.9 illustrates the estimated market relevance of selected example configurations for large-segment BEVs, differentiated by battery technology, model year, and range option, as classified by the OEM agent. All configurations in this segment assume all-wheel drive by two electric motors, in line with typical drivetrain setups for this vehicle class. The underlying vehicle data such as average battery capacity, energy consumption, range, and price are provided in Table C.6.

In the large segment, LFP batteries show relatively high market relevance in the current market and near future. However, their importance declines over time as vehicle range requirements increase and alternative technologies become more competitive. NMC continues to play a central role, maintaining strong and steady market relevance across all years. Solid-state batteries begin to gain traction once they reach technological maturity and become cost-competitive, contributing significantly to market relevance from 2030 onward especially in long-range configurations.

Data availability

Data will be made available on request.

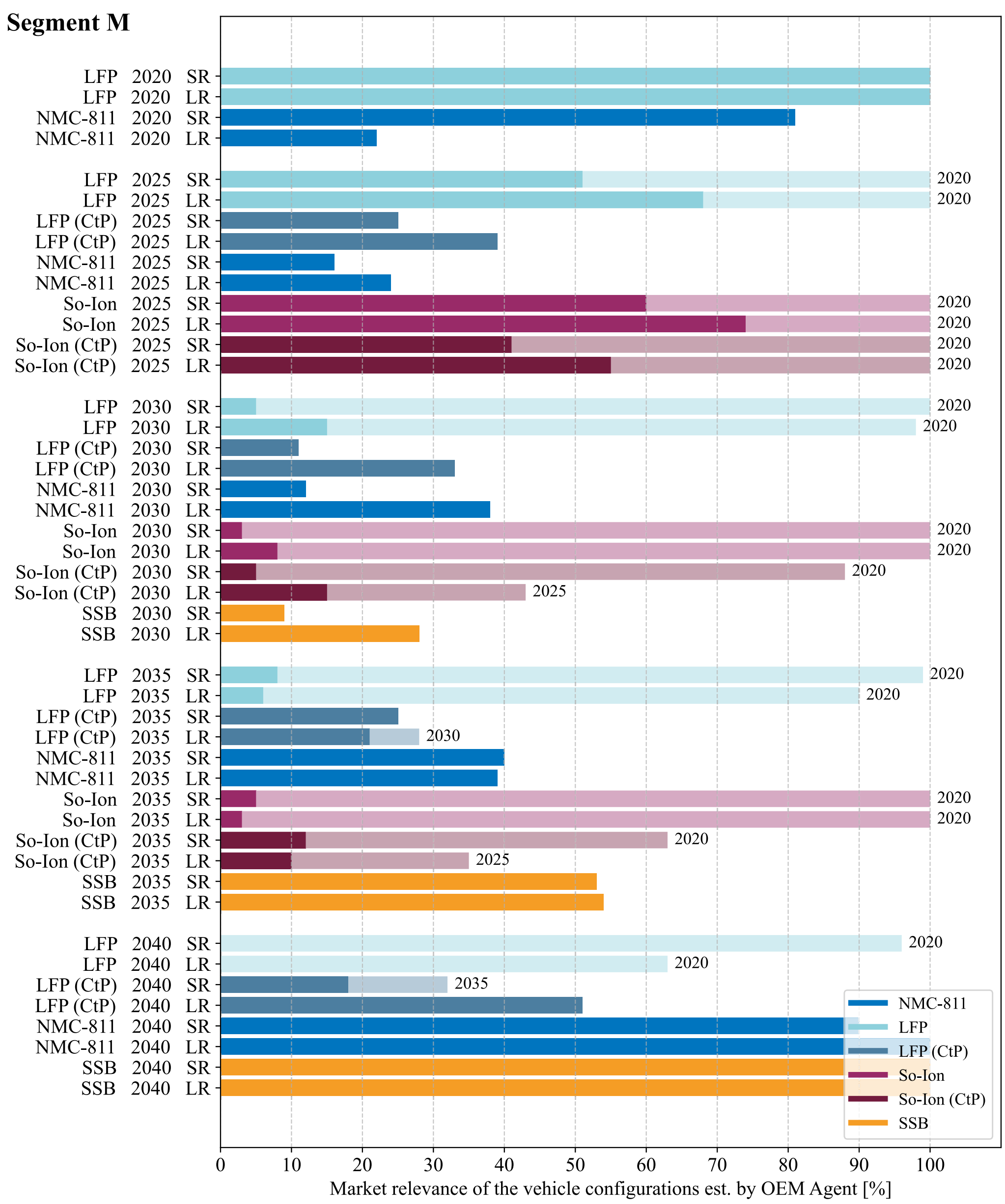

Fig. C.8. Market relevance of various example vehicle configurations with future battery technologies for different model years in the medium segment based on estimations of the OEM agent. The transparent bars illustrate the probability of models that are more likely to enter the market in an earlier year than in the year in which they are technically feasible.

Table C.6
Technical specifications and market relevance as estimated by the OEM agent (P%) of the example vehicle configurations in the large segment as displayed in Fig. C.9.

Segm.	Year	Battery chemistry	Vehicle version	Capacity [kWh]	Consumption [kWh/100 km]	Range [km]	Price [EUR]	P%
L	2020	LFP	SR[a]	51	16.9	304	65.406	100
		LFP	LR[b]	63	17.5	362	68.382	100
		NMC-811	SR	84	17.1	489	75.943	100
		NMC-811	LR	103	17.7	583	81.342	80
	2025	LFP	SR	56	15.9	350	63.982	92
		LFP	LR	68	16.4	418	66.630	95
		LFP (CtP)	SR	90	16.3	557	71.219	87
		LFP (CtP)	LR	111	16.8	662	75.531	92
		NMC-811	SR	99	16.2	610	75.481	74
		NMC-811	LR	121	16.7	726	80.773	81
		So-Ion	SR	33	15.4	218	63.526	88
		So-Ion	LR	41	15.8	262	66.069	90
		So-Ion (CtP)	SR	54	15.7	348	70.476	80
		So-Ion (CtP)	LR	67	16.1	416	74.617	83
	2030	LFP	SR	60	14.8	403	61.871	39
		LFP	LR	74	15.3	482	64.034	67
		LFP (CtP)	SR	97	15.2	641	67.781	77
		LFP (CtP)	LR	120	15.7	763	71.303	94
		NMC-811	SR	114	15.2	748	73.310	78
		NMC-811	LR	140	15.7	890	78.104	95
		So-Ion	SR	42	14.4	291	57.954	18
		So-Ion	LR	51	14.7	349	59.215	34
		So-Ion (CtP)	SR	68	14.7	464	61.401	42
		So-Ion (CtP)	LR	84	14.6	577	62.268	50
		SSB	SR	120	15.0	796	85.376	47
		SSB	LR	147	15.5	950	92.945	77
	2035	LFP	SR	60	13.8	433	61.715	2
		LFP	LR	74	14.2	518	63.841	4
		LFP (CtP)	SR	97	14.2	689	67.526	18
		LFP (CtP)	LR	120	14.6	820	70.989	43
		NMC-811	SR	114	14.2	803	72.417	36
		NMC-811	LR	140	14.6	956	77.005	70
		So-Ion	SR	42	13.4	312	57.734	1
		So-Ion	LR	51	13.7	375	58.945	1
		So-Ion (CtP)	SR	68	13.7	498	61.044	4
		So-Ion (CtP)	LR	84	14.0	597	63.016	9
		SSB	SR	120	14.0	855	82.556	41
		SSB	LR	147	14.4	1020	89.475	76
	2040	LFP	SR	60	12.8	467	61.558	0
		LFP	LR	74	13.2	559	63.648	0
		LFP (CtP)	SR	97	13.1	743	67.271	0
		LFP (CtP)	LR	120	13.5	886	70.675	48
		NMC-811	SR	114	13.1	867	71.524	66
		NMC-811	LR	140	13.5	1033	75.907	100
		SSB	SR	120	13.0	922	80.048	96
		SSB	LR	147	13.4	1102	86.392	100

[a] Standard range.
[b] Long range.

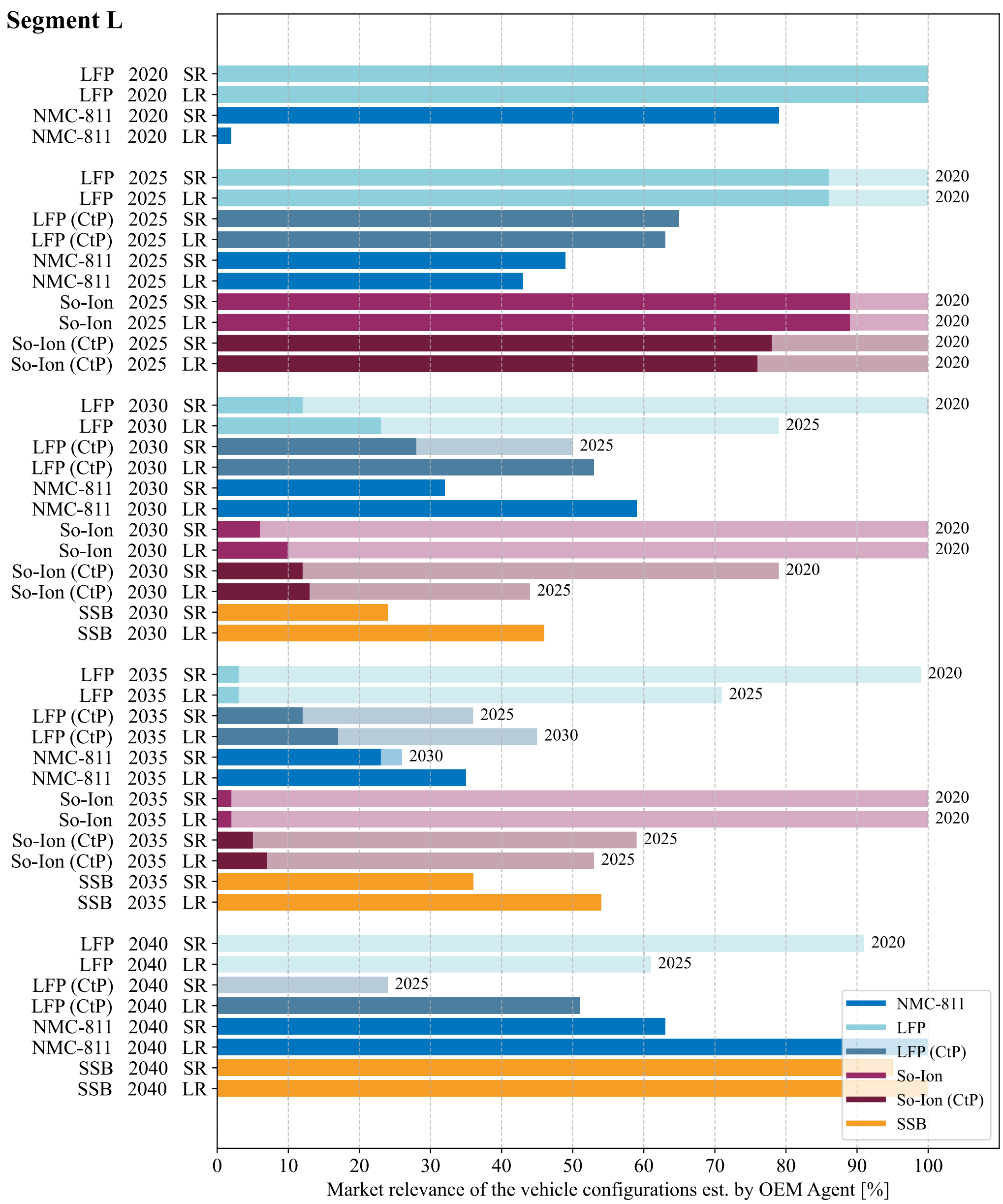

Fig. C.9. Market relevance of various example vehicle configurations with future battery technologies for different model years in the large segment based on estimations of the OEM agent. The transparent bars illustrate the probability of models that are more likely to enter the market in an earlier year than in the year in which they are technically feasible.

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