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Dynamic battery warranty for electric vehicles: Increase customer confidence and extend vehicle utility

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Executive Summary

Electric Vehicle (EV) battery warranties are given to provide confidence to buyers and encourage EV sales. However, these warranties are often very simplistic and do not consider vehicle usage or driving behavior differences. As a result, some customers are overpaying while others are underpaying for the coverage that they receive. This study critically examines current EV battery warranties using a lithium-ion battery degradation model alongside EV energy consumption to evaluate warranty effectiveness under various usage conditions. Simulating 48 distinct scenarios reveals diverse degradation patterns, suggesting that warranties could be improved by differentiating based on these conditions. It also highlights limitations, such as the absence of coverage for vehicle-to-grid (V2G) technology.

To address these issues, a dynamic battery warranty is proposed, designed to align driver incentives with battery lifetime considerations without increasing risks for EV manufacturers.

Keywords: V2H &V2G, Electric Vehicles, Batteries, Public Policy & Promotion, Business models for vehicle sales

1 Introduction

Electric vehicles (EVs) are increasingly recognized as pivotal in the global effort to mitigate climate change and decarbonize the transportation sector. However, despite significant technological maturation and supportive government incentives, the widespread adoption of EVs faces ongoing challenges. As of 2024, purely electric vehicles represented only 14.5% of new vehicle sales in Europe [1] , indicating that substantial barriers remain. Among the primary concerns for prospective buyers is the uncertainty surrounding the long-term performance and lifespan of the EV battery [2], [3]. The battery constitutes a significant portion of the vehicle's total cost [4], making its durability and potential replacement cost a critical factor in the purchasing decision. This apprehension acts as a barrier to broader EV acceptance. Consequently, maximizing battery longevity and providing consumers with confidence in battery performance are key challenges for the industry.

To address consumer concerns and mitigate the financial risk associated with battery degradation, Vehicle Original Equipment Manufacturers (OEMs) provide warranties. These typically guarantee a minimum battery State of Health (SOH), often defined as retaining around 70% of the original capacity, for a specified duration or accumulated mileage – common figures being 8-10 years and 160,000 km (approx. 100,000 miles), whichever threshold is reached first. In a highly competitive market, offering more generous warranty terms (extended time or mileage) can serve as a significant differentiating factor for OEMs.

Despite their importance, current warranty structures exhibit several limitations.

- **Simplified Degradation Assumption:** Battery degradation is a complex phenomenon influenced by both time (calendar aging) and usage intensity (cycle aging). Key operational factors such as ambient temperature, average State of Charge (SOC), Depth of Discharge (DoD), and charging/discharging rates (C-rate) significantly affect the rate of degradation [5]. Standard warranties, however, often implicitly assume a uniform degradation rate or average usage profile across all users, which rarely reflects the diverse real-world operating conditions.
- **Potential Inconsistencies:** Warranty terms sometimes appear driven more by market positioning than precise, data-driven lifetime predictions. For example, offering the same mileage warranty (e.g., 160,000 km) for vehicle variants with substantially different battery capacities and ranges is questionable, as the smaller-range vehicle will inherently undergo more cycles to cover the same distance, potentially leading to faster degradation.
- **Inadequate Coverage for Vehicle-to-Everything (V2X):** The emergence of V2X technologies– including Vehicle-to-Grid (V2G), Vehicle-to-Home (V2H), and Vehicle-to-Load (V2L) – presents a new challenge. These functionalities utilize the EV battery for stationary energy applications, contributing to cycle aging independently of mileage accumulation. Current mileage-based warranties generally fail to account for, or explicitly exclude, degradation resulting from such stationary use. This creates a coverage gap and introduces uncertainty, potentially hindering the adoption of V2X capabilities despite developed standards (e.g., ISO 15118-20 for V2G communication) and their potential economic and grid benefits. Some studies suggest calendar aging dominates [6], implying V2X might be feasible without excessive harm, but warranty ambiguity remains a barrier.
- **Lack of User-Specific Adaptation:** Because current warranties don't typically account for individual usage patterns (e.g., frequency of fast charging, typical driving environment temperatures, V2X usage), they may be overly conservative for some users and insufficient for others. This one-size-fits-all approach lacks fairness and transparency regarding how usage impacts long-term battery health and warranty validity.

Addressing these shortcomings necessitates a move towards more sophisticated warranty models that better reflect the nuances of battery degradation. While various methods exist for modeling battery degradation, ranging from detailed electrochemical models to data-driven approaches, empirical models based on fitting equations to experimental data are common [7] and provide a basis for developing practical warranty structures. In the stationary energy storage sector, performance-based warranties already exist, often guaranteeing a minimum SOH per period under specified operating conditions. Adapting such concepts to the dynamic and varied use patterns of EVs presents a challenge, requiring a balance between accuracy, measurability, transparency, and user-friendliness. It is crucial that any proposed warranty clearly defines how operating conditions and SOH are measured, and by whom, ensuring fairness for both the consumer and the OEM. Some manufacturers are beginning to explore options like conditional warranty extensions, potentially tied to maintenance or subscription services, indicating an industry awareness of the need for more flexible solutions.

This study leverages battery degradation and EV energy consumption models to critically evaluate the limitations of current EV battery warranties. Building upon this analysis, the paper proposes and explores the concept of a "dynamic warranty" framework that adapts warranty coverage based on actual battery usage patterns. Specifically, this work will:

1. Highlight the shortcomings of standard fixed time/mileage warranties under diverse, realistic user profiles.
2. Propose and analyze several potential dynamic warranty structures, considering their positive impacts and implementation challenges.

The aim is to contribute to the development of fairer, more transparent, and technologically informed battery warranty solutions that can enhance consumer confidence, reduce battery degradation, and support V2X integration.

2 Methodology

Two models are used: one for vehicle energy consumption and another for battery degradation. Vehicle consumption can be modeled in various ways, such as using physical equations. In this study, data from a simulator of the Nissan Leaf 62 kWh is used to model EV consumption [8]. A simple model (Eq.(1)) is developed to estimate consumption (C) under different speed (v) and temperature (T) conditions, based on the data collected from the simulator. Figure 1 illustrates how vehicle consumption varies depending on these conditions.

$$C\left[\frac{kWh}{km}\right] = 0.2345 - 2.09 \cdot 10^{-3} v + -4.08 \cdot 10^{-3} v^2 + 2.46 \cdot 10^{-5}\, T + 4.51 \cdot 10^{-6} v \cdot v + 9.94 \cdot 10^{-5} T^2 \quad (1)$$

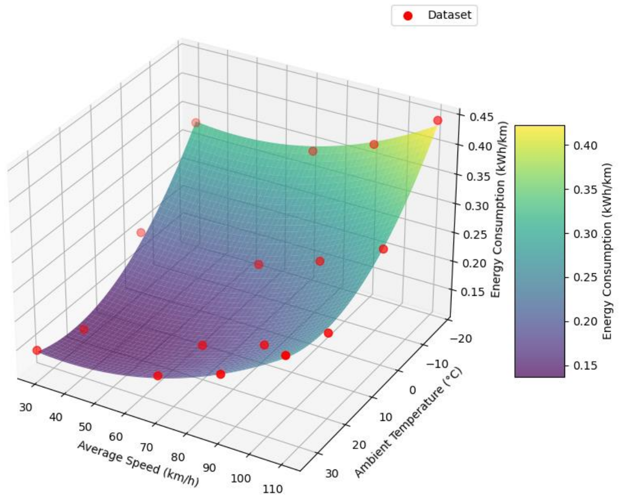

Figure 1: Nissan Leaf 62 kWh Energy Consumption at different temperatures and speeds.

To analyze battery degradation, a battery lifetime model is used. The model referenced in this study, sourced from the literature, was developed for a lithium iron phosphate (LFP) cell. It accounts for two types of aging: calendar aging, which depends on time[9] and cycling aging, which depends on the Full Equivalent Cycles (FEC) the battery undergoes [10]. The models, shown in Eqs (2)-(8) with parameters from Table 1, consider the main stress factors: State of Charge (SOC), Temperature (T), Depth of Discharge (DOD), and C-rate. Total degradation is calculated as the sum of both aging effects. The models yield a Mean Absolute Error (MAE) of 3.1%

$$C_{fade}^{cal} = k_{temp} * k_{SOC} * \sqrt{t} \quad (2)$$

$$k_{temp} = k_{ref} \cdot exp\left(-\frac{E_a}{R} \cdot \left(\frac{1}{T} - \frac{1}{298.15}\right)\right) \quad (3)$$

$$k_{SOC} = e \cdot (SOC - 0.5)^3 + f \quad (4)$$

$$C_{fade}^{cyc} = k_{crate} \cdot k_{DOD} \cdot \sqrt{FEC} \quad (5)$$

$$FEC = \frac{Energy\ charge + Energy\ Discharge}{Nominal\ Energy\ Capacity} \quad (6)$$

$$k_{crate} = a \cdot C_{Rate} + b \quad (7)$$

$$k_{DOD} = c \cdot (DOD - 0.6)^3 + d \quad (8)$$

Table 1: Battery degradation model parameters.

a	0.0630	***c***	4.0253	**e**	2.8575	**kref**	0.0012571
b	0.0971	***d***	1.0923	***f***	0.60225	**Ea**	17126

Once vehicle consumption and battery degradation models are defined, different scenarios are designed to explore how battery degradation may occur under varying conditions. Scenarios are designed by combining the parameters in Table 2: two average temperatures, yearly driving mileage, average speed, three DOD and SOC conditions, and the option to use V2G for over 20 years. The intensity of V2G operations has a direct effect on battery degradation. In simulations where V2G is implemented, a daily additional discharge equivalent to 30% of the DOD is assumed. This results in 48 scenarios simulated to evaluate battery degradation under varying usage conditions.

Table 2: Simulation parameters.

Monthly Average Temperature	Barcelona, Gothenburg
Driving per year	10 000 km, 20 000 km
DOD and SOC	(80, 60), (50, 75), (20, 90)
Average Speed	70, 110
V2G	Yes, No
Time	20 years

After analyzing current warranty limitations, different warranty strategies are compared. These strategies are:

- **Conventional Fixed Warranty:** This strategy defines a fixed number of kilometers and a time, guaranteeing a minimum SOH at the end of the warranty. The degradation model can be used by assuming worst-case stress factors to calculate how much battery degradation occurs under extreme conditions. The warranty is reflected in Eqs (9)-(10). Since degradation comprises both calendar and cycling aging, and the warranty includes both time and kilometers, one must be fixed to estimate the other. For example, the calendar degradation over 10 years can be calculated, and the remaining degradation up to the guaranteed SOH (e.g., 70%) can be assigned to cycling. To translate cycles into kilometers, the worst estimated energy consumption (e.g., kWh/km) can be used. This ensures a conservative warranty design by assuming low efficiency, which leads to fewer kilometers per cycle. Moreover, this enables trade-offs like offering more years with fewer kilometers or vice versa.

$$C_{fade\,MAX}^{total} = C_{fadeMAX}^{CAL} + C_{fadeMAX}^{CYC} \quad (9)$$

$$SOH_{warranty} = 1 - C_{fade\,MAX}^{total} \quad (10)$$

- **Energy Throughput-Based Warranty (kWh):** This warranty replaces kilometers with energy throughput (kWh), making it compatible with V2G and other V2X technologies. It can also be given as FEC. This warranty accounts for varying driving styles by penalizing higher energy consumption. Although consumption is not directly considered in the warranty, estimated consumption profiles can be included to help users translate kWh into approximate km in vehicles without V2X functionality. For warranty modeling, the same worst-case approach used in the basic warranty can be applied.

- **SOH Evolution Profile Warranty:** Rather than just guaranteeing a minimum SOH at the end of a period, this strategy informs users about how SOH is expected to evolve. It enables visibility into whether degradation is expected to occur rapidly at the beginning and then slow down, or remain stable and degrade sharply later. This profile is generated using the degradation model under the worst-case stress conditions for each year, considering kWh or km caps based on usage intensity. Minimum SOH values are guaranteed per year, and different numbers of full equivalent cycles per year can be considered.

- **Dynamic Warranty Using Look-Up Tables:** This strategy adapts based on the SOH profile. In this case, information about stress factors (Sf) that affect degradation is incorporated. The influence of individual stress factors can be shown or hidden depending on their relevance to the battery or user. For example, if the battery operates in a temperature-controlled environment, temperature may be excluded. The impact of each stress factor can be evaluated by comparing it to worst-case scenarios, as defined by Equations (11)-(12). The figure displays the normalized impact of each stress factor, illustrating how capacity fade can be reduced by operating the battery under less stressful conditions.

$$Sf = \{\mathrm{C-rate}, \mathrm{Depth\ of\ Discharge}, \mathrm{SOC}\ , \mathrm{T}\} \tag{11}$$

$$Sf_{norm} = \frac{k_{Sf}}{kMAX_{Sf}} \tag{12}$$

Due to the nonlinear nature of capacity fade, where the rate of degradation decreases over time, the order of exposure to stress factors matters—early exposure has more impact than later exposure. To simplify calculations, it is proposed to use the average of the stress factors over a fixed warranty update window, typically one year, following equation (13) for the calendar factors and equation (14) for the cycling factors. A smaller time window provides a more precise estimation of degradation by better preserving the temporal impact of stress factors. However, shorter windows may overly complicate control for OEMs and communication with customers. Additionally, to improve precision, the warranty can be divided into calendar and cycling components, splitting both the time window and the calculations accordingly.

Previous approaches already included a conservative bias, assuming worst-case stress levels that rarely occur continuously in real use. With dynamic warranties and simplification through the averaging of impact factors, it is now recommended to include an additional safety factor—especially during the first year or initial cycles, when the degradation rate is higher. The MAE of the battery lifetime model can serve as a useful metric for determining the safety factor. Equation (15) reflects the full expression of the SOH Dynamic Warranty.

$$\overline{Sf_{SOC,T}} = \frac{\sum Sf \cdot \Delta t}{\sum \Delta t} \tag{13}$$

$$\overline{Sf_{DOD,C-rate}} = \frac{\sum Sf \cdot \Delta FEC}{\sum \Delta FEC} \tag{14}$$

$$\text{SOH Dynamic Warranty} = 100\text{-}\ \overline{Sf_{SOC,T}} \cdot C_{fadeMAX}^{CAL} + \overline{Sf_{DOD,C-rate}} \cdot C_{fadeMAX}^{CYC}\text{-MAE} \tag{15}$$

3 Results

3.1 Current Warranties limitations

Significant variability in battery degradation is observed after evaluating the 48 scenarios over a 20-year simulation period. As shown in Figure 2, capacity fade at the end of the simulation ranged from 18.09% to 32.97%, confirming that battery degradation is highly dependent on usage patterns, including charging cycles, energy throughput, and the specific conditions under which the battery is operated.

Although the models may not perfectly represent all battery packs, the results indicate that the degradation rates predicted by the model are consistently lower than the thresholds set by EV battery manufacturers in their warranties for 160000km and 10 years. This discrepancy is likely due to the conservative safety factors manufacturers apply to ensure reliability and avoid potential warranty claims.

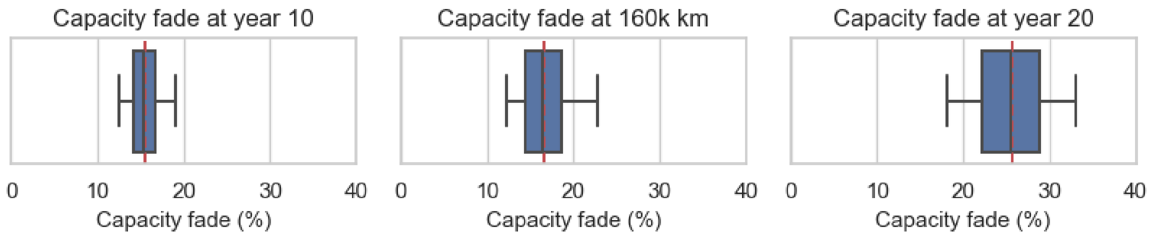

Figure 2: Capacity fade statistics of 48 scenarios simulated

Figure 3 presents eight scenarios to illustrate differences in simulation parameters. For instance, Gothenburg experiences less degradation than Barcelona under identical conditions, due to lower temperatures reducing calendar aging. Paradoxically, while the vehicle range in Gothenburg is lower than in Barcelona (due to higher energy consumption and internal battery losses), the overall capacity fade is less pronounced. This paradox illustrates that, from a user perspective, it would be beneficial to display the State of Health (SOH) of the battery alongside the expected vehicle range under different conditions. Doing so would provide a more comprehensive understanding of battery performance over time.

The degradation curves reveal a non-linear trend. Current warranties lack clarity on SOH progression, which creates uncertainty for EV buyers. Batteries with a slower initial decline in SOH retain higher value, even if the final SOH is similar.

A battery that maintains a higher SOH for longer has more value than one that degrades quickly at the beginning, even if both reach the same endpoint. This suggests that warranties should not only specify the final degradation limit (such as 70% capacity) but also clarify how the degradation rate might progress over time, providing users with a clearer picture of long-term battery health.

Additionally, V2G technology is also evaluated as part of degradation analysis. The results show that batteries subjected to daily V2G usage show increased degradation per kilometer but decreased degradation per cycle, highlighting the importance of cycle-based degradation assessment. This suggests that V2G usage, while contributing to overall degradation, enables more efficient use of the battery by extracting additional performance over the same lifespan. However, manufacturers do not address the effects of V2G in their warranties, leaving a gap in coverage for users who engage in regular V2G operations.

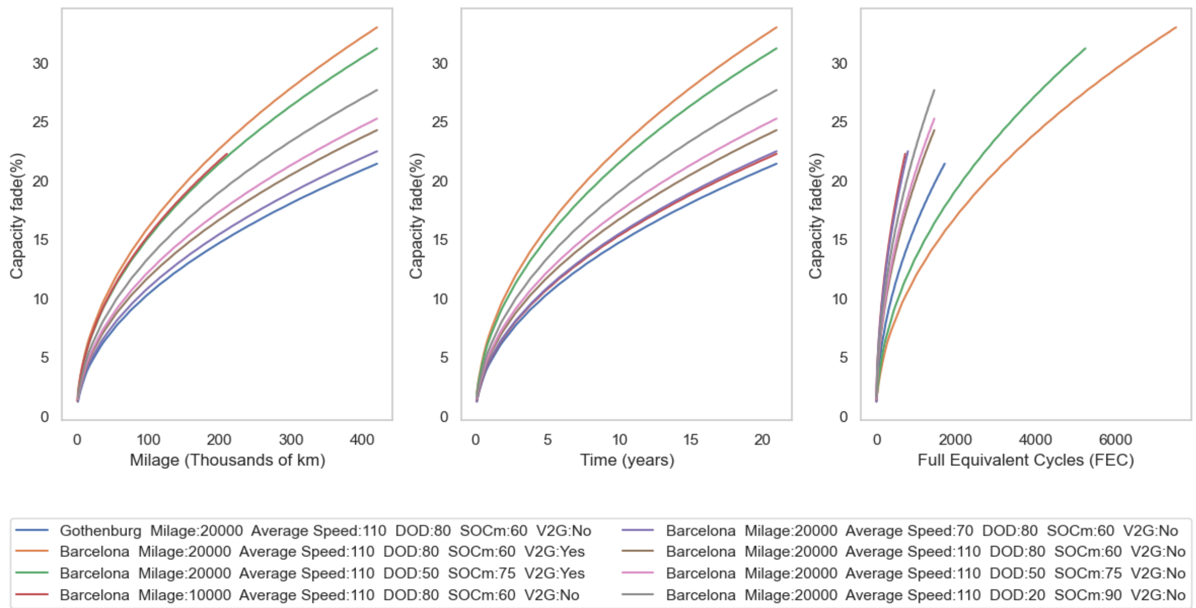

Figure 3: Capacity fade (%) vs Mileage, Time, and FEC for 8 different simulations.

3.2 Proposal Dynamic Battery Warranty

To compare the performance of the proposed warranty strategies, a case study under dynamic operating conditions is evaluated.

For the conventional warranty, the degradation model is applied by fixing the period under warranty to nine years. Over this period, calendar aging, under the most extreme stress factors, results in a degradation of 23.9%. With the remaining 6.1% margin before reaching the standard warranty threshold of 70% SOH, it is estimated that approximately 800 additional FECs can be sustained due to cycling-induced degradation. If expressed in conventional units (kilometers), these 800 FECs would correspond to approximately 165,000 km, assuming an average energy consumption of 0.30 kWh/km.

The Energy Throughput-Based Warranty is equivalent in coverage to the conventional warranty, but expressed in kilowatt-hours (kWh) instead of kilometers, thereby enabling compatibility with V2G technologies.

The SOH Evolution Profile Warranty is presented in the Table 3. It has been calculated assuming worst-case degradation and a fixed number of cycles per year. Various cycles per year scenarios can be given for the warranty. An alternative is that this warranty model could be combined with the conventional approach in cases where the yearly cycle limit is exceeded.

Table 3: Warranty annual SOH Coverage- Profile Warranty.

FEC/Year	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Year 5**	**Year 6**	**Year 7**	**Year 8**	**Year 9**
50	90	86	83	80	77	75.5	73.6	72	70
175	89	84	80	77	74	72	70	-	-

For the dynamic warranty, the first step involves calculating the look-up tables. Figure 4 presents these tables, illustrating how the reduction factors (Sf) vary for each of the stress factors. In general, lower values of C-rate, DOD, temperature, and SOC are associated with reduced battery degradation. Among these, SOC is the most influential factor, capable of reducing degradation by more than 70%.

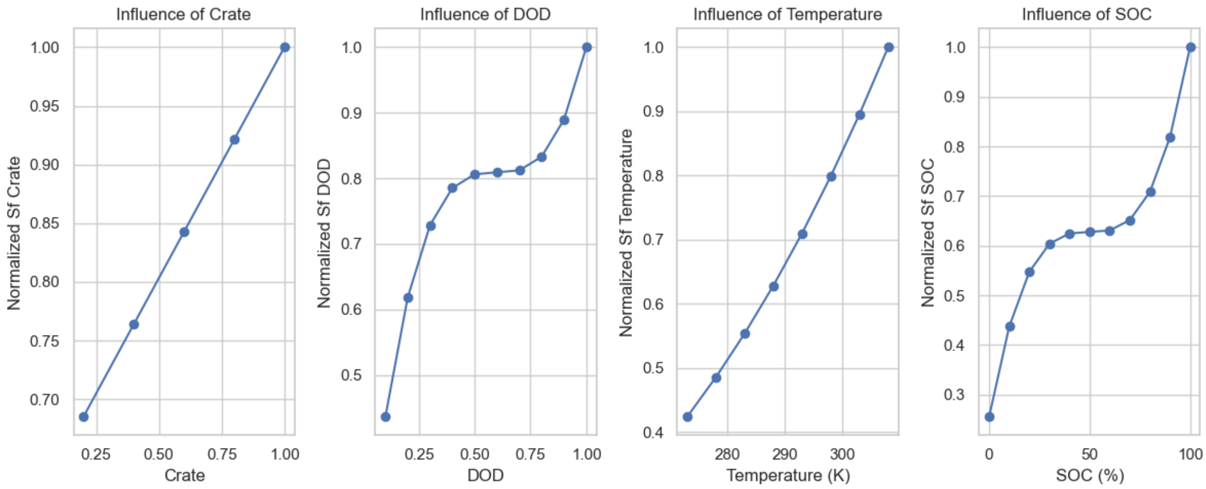

Figure 4: Influence of each Stress Factor. Normalized values.

To apply stress factors, it is necessary to gather data on how the battery was used during the evaluation period, typically one year. The most effective method is through histograms, like those shown in Figure 5, which capture either the number of cycles or the percentage of time spent under different operating conditions. After applying the weighted averaging process, the resulting normalized stress factors for the data of Figure 5 are: 0.737 for SOC, 0.773 for temperature, 0.747 for C-rate, and 0.750 for DOD.

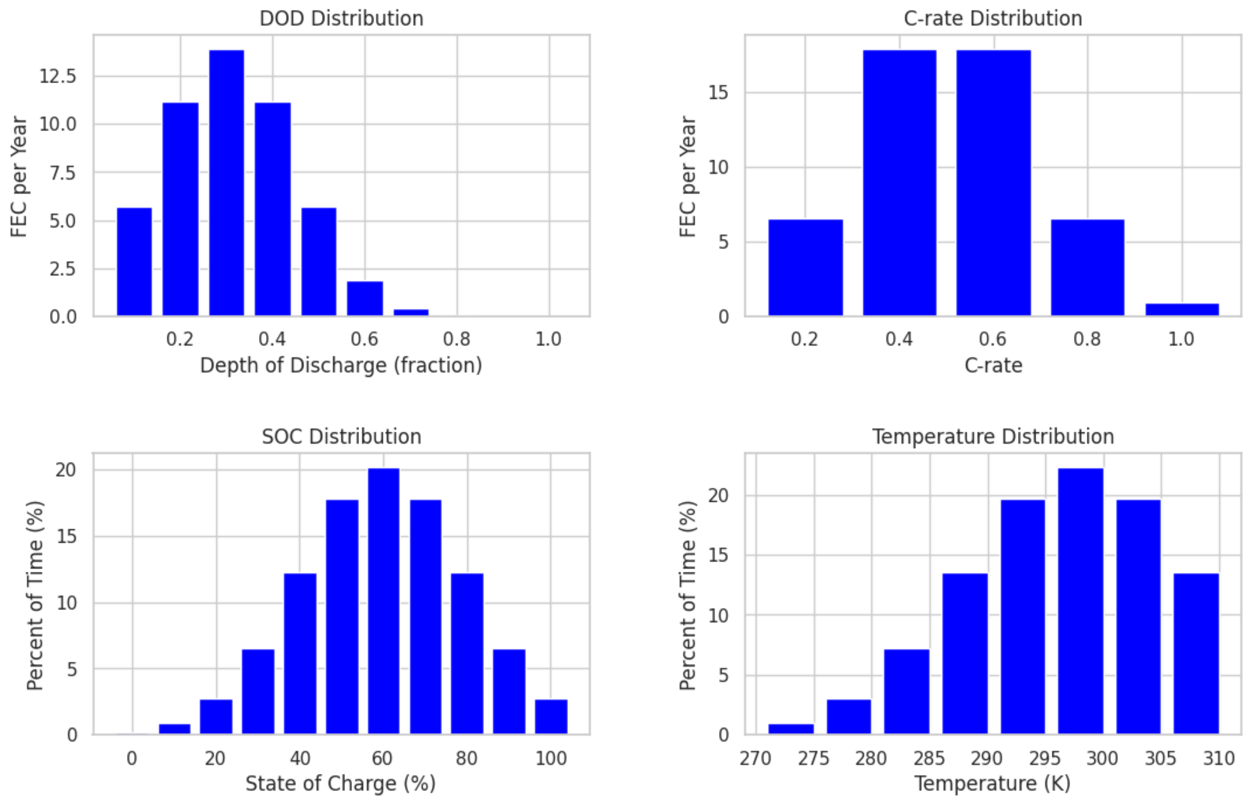

Figure 5: Compilation of Stress Factors Using Histograms for Dynamic Warranty Analysis.

Figure 6 shows a comparison among the three warranty types. The shaded area represents the combinations of SOH with kWh or years where the battery is covered by the warranty and is therefore eligible for repair or replacement. The larger this area, the greater the benefit and reassurance for the user. A substantial difference can be observed between the dynamic warranty and those based on worst-case assumptions. This supports findings from previous simulations, which showed that current warranty strategies tend to be overly restrictive. Moreover, the dynamic warranty ensures that after more than 25 years and over 1,500 cycles, the battery's SOH will remain above 75%. If the vehicle does not support V2G, this would correspond to more than 310,000 km, providing strong reassurance to users regarding the long-term reliability of electric vehicles.

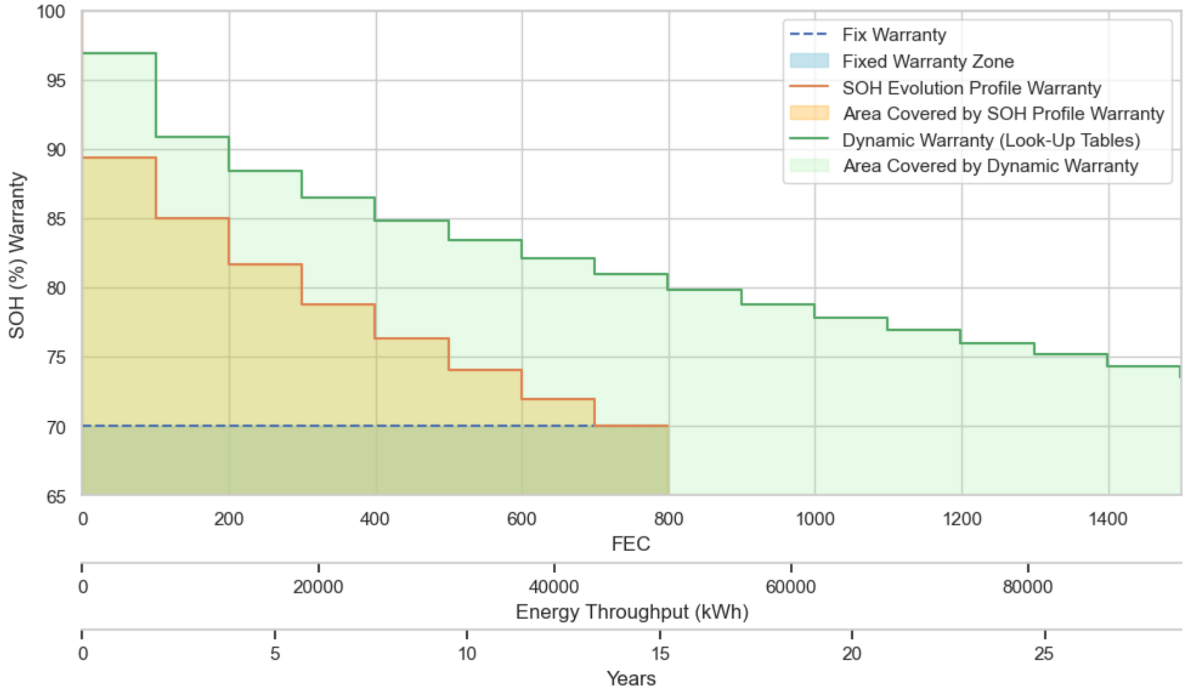

Figure 6: Comparison of Different Warranty Strategies

4 Conclusions

Current warranties have limitations that go beyond the safety factors set by OEMs. The kilometer-based limits do not accurately capture the true impact of cycling degradation, which is better measured in kilowatt-hours consumed or FEC. This also restricts the integration of V2G technologies and limits the extension of battery warranties to other applications if the vehicle reaches the end of its life before the battery warranty expires.

The dynamic warranty proposed addresses these challenges by shifting the focus from kilometers to cycles. Dynamic warranties enable tracking of battery degradation throughout its lifecycle and enhance optimization by providing insights into how various factors affect degradation. Additionally, the dynamic warranty offers consumers an incentive to prioritize battery health in their decision-making process.

Building confidence in battery lifetime models is key for OEMs to offer dynamic warranties and, therefore, extend coverage without incurring additional costs.

Finally, simplicity and understandability are essential to drive market adoption. This paper also explores practical strategies for the implementation of dynamic warranties. These include structural changes (e.g., offering a traditional warranty but also offering an extension using the dynamic warranty that is based on usage) as well as financial changes (e.g., rebate structures for leased vehicles based on SOH). These can further bolster customer confidence while encouraging health-conscious usage.

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Presenter Biography

Tomás Montes is an Industrial Engineer by the University of Oviedo. During the last three years he has been working as a researcher at the Catalonia Institute for Energy Research (IREC) in the Energy System Analytics group, he has specialized in developing battery lifetime models and using them to optimize the use of batteries. In addition, he has experience analyzing the possibilities of the batteries after their first life. In this context, he is carrying out his PhD covering different decision algorithms during the life cycle of the batteries.