

Empirical calendar aging model for LFP and NMC EV batteries – Romanian case study

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Abstract. The forecasting of large volumes of retired electric vehicle (EV) batteries has intensified the efforts of repurposing the ones with remaining usable capacity in different second-life applications, including as battery energy storage systems. This paper analyses the potential of repurposing the retired batteries of the most commercialized EV model in Romania by approximating the remaining usable capacity. An empirical calendar aging model is applied considering the chemistry, nominal usable capacity and calendar warranty period when the battery temperature is 25°C, 35°C and 45°C. Moreover, in each scenario four urban driving styles are presumed, with different values for State-of-Charge (SoC): 40%, 50%, 60% and 70%. The results show that the remaining usable capacity depends not only on chemistry, but also on stress factors like operational temperature, charging strategy and driving behaviour. The available capacity for second-life applications varies from 23.97 kWh, for best case scenario, to under 10 kWh, for intensive degradation, implying the need for a rigorous sorting methodology for retired batteries

1 Introduction

Global electric vehicle (EV) sales exceeded 17 million in 2024, with over 1.1 million new registrations in European Union (EU) countries, continuing the efforts to achieve climate neutrality by 2050 [1]. Romania started adopting EVs in 2020, when the EV market share surpassed 2%, as presented in Figure 1. The upward trend maintained until 2023, when it reached the highest share of 10.7%, with over 15000 new battery electric vehicle (BEV) registrations. Due to reduced financial incentives and increased taxes, the number of new BEV registrations decreased in 2024 and 2025 [2].

At the end of 2025, there were a total of 53562 EVs registered in 2020-2025 timeframe [2]. Although the increase in EV market share sustains and promotes low-carbon transportation alternatives, it also raises concerns about battery decommissioning and disposal at the end of lifetime. Thus, ongoing efforts are being made to repurpose the ones with remaining capacity in second-life applications. The remaining capacity depends on both calendar and cycle aging [3]. The capacity loss due to cycle aging depends on State-of-Charge (SoC), operational battery temperature (T), depth of discharge (DoD) and cycle number, while calendar aging is related to time, T and SoC [4].

The aging models used to simulate the degradation behaviour of EV batteries can be classified in empirical, semi-empirical and physico-chemical [5]. More recent

approaches include machine-learning, statistical and data driven models for high accuracy prediction [6].

This paper estimates the remaining usable capacity of retired EV batteries by applying an empirical calendar aging model on the most commercialized EV model in Romania. There are other studies that investigated the capacity loss due to calendar aging of EV batteries. Yang et.al. proposed in [7] a multi-factor and cross-factor experimental matrix to determine the influence of SoC, T and pressure on calendar and cycle aging of Lithium Iron Phosphate (LFP) EV batteries. The results shown that calendar aging is strongly influenced by SoC and T. As the values increase, the capacity fade becomes more pronounced.

Liu et.al. analysed in [8] the aging characteristics of combined battery systems and proposed an innovative deep reinforcement learning framework to determine the costs of battery degradation in several vehicle-to-grid scenarios considered in China.

Najera et. al. investigated in [9] the modelling process of LFP and Nickel Manganese Cobalt Oxide (NMC) chemistries to determinate the capacity decay caused by calendar and cycling aging. The online proposed model considered T, SoC and charge/discharge rate as main parameters. The results indicated that the model offers enhanced versatility and functional capability, with errors below 5% between the theoretical and measured values.

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The objective of this study is to investigate the potential of repurposing the retired BEV batteries in second-life applications in Romania. Based on a calendar aging model, the remaining battery capacity is estimated considering the chemistry, nominal capacity, other technical parameters that characterized the battery of the most commercialized BEV and the stress factors that influence degradation (SoC and T).

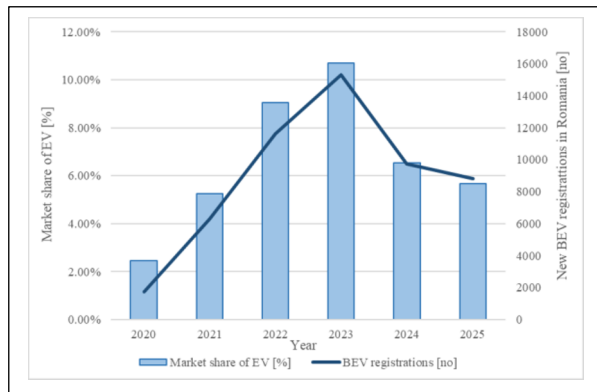


Fig. 1. EV market share evolution in Romania between 2020 and 2025 [2]

2 Calendar aging methodology

The proposed methodology includes five steps. First, a market analysis is performed to determine the most commercialized BEVs in Romania and their market share. Then, the chemistries, nominal capacity, warranty period and other technical parameters of the most sold BEV are determined. Based on the initial data, the calendar aging model is applied to establish the remaining capacity of retired BEV batteries.

The calendar capacity loss Q_{loss}^{cal} [%] depends on SoC , T [K] and battery warranty period t [days]. These stress factors may vary, depending on battery chemistry, and can have a significant impact on calendar aging. Q_{loss}^{cal} is given in (1) [8 - 10].

$$Q_{loss}^{cal} = \alpha_1 \cdot \exp(\alpha_2 \cdot SoC) \cdot \exp\left(\frac{\alpha_3}{T}\right) \cdot t^{\alpha_4} \quad (1)$$

where α_1 , α_2 , α_3 and α_4 coefficients are depending on the battery chemistry. The values considered in this study are presented in Table 1.

Table 1. Degradation coefficients of analysed chemistries [8]

Coefficient	LFP	NMC
α_1	$5.98 \cdot 10^6$	$1.14 \cdot 10^{12}$
α_2	0.69	4.7
α_3	$-6.46 \cdot 10^{-3}$	$-10.8 \cdot 10^{-3}$
α_4	0.5	0.5

In the next step, the scenarios must be defined. Three scenarios were analysed based on operational temperature of the BEV batteries. In each scenario four different values are considered for SoC, as presented in Table 2.

Table 2. Considered scenarios for analysing the remaining capacity of retired BEV batteries

Scenario	Temperature	SoC=4 0%	SoC=5 0%	SoC=60 %	SoC=7 0%
1	$T_1 = 25$ °C	0.4	0.5	0.6	0.7
2	$T_2 = 35$ °C				
3	$T_3 = 45$ °C				

In the final step, the remaining capacity C_{cal} [%] is calculated with (2) [11]. To determinate a numerical value, the obtained percentage must be multiplied by the nominal usable capacity of the BEV battery, provided in the technical sheet by the manufacturer.

$$C_{cal} = 100 - Q_{loss}^{cal} \quad (2)$$

3 Results

To identify the most commercialized BEV model in Romania, a market analysis was performed. The results revealed that between 2020 and 2025, there were over 53500 new BEV registrations. From 160 BEV models, only 9 exceeded 1000 registrations in the analysed period and are presented in Table 3.

Table 3. Top 9 BEV models in Romania, considering the number of registrations [2]

BEV model	2020	2021	2022	2023	2024	2025	Total
Spring (Dacia)	0	3068	6830	6875	3263	1596	21632
Model 3 (Tesla)	32	218	759	1022	1679	604	4314
Model Y (Tesla)	1	2	261	2079	846	505	3694
Kona (Hyundai)	161	384	365	445	367	618	2340
UP! (Volkswagen)	161	435	514	488	34	0	1632
Megane (Renault)	0	0	154	818	297	209	1478
ID.3 (Volkswagen)	102	291	180	481	142	151	1347
ZOE (Renault)	426	347	269	127	77	1	1247
ID.4 (Volkswagen)	0	245	157	318	148	216	1084

Table 4. Main technical parameters of Spring model [2]

BEV model	Electric 100	Electric 65
Battery type	Lithium-ion	Lithium-ion
Cathode material	LFP	NMC
Usable capacity [kWh]	24	25
Warranty period [years]	8	8
Warranty mileage [km]	120000	120000
Electric range [km]	160	160
Vehicle consumption [Wh/km]	150	156

As it can be observed, Spring model from Dacia, a Romanian car manufacturer, is the most sold BEV, with an approximately 40% BEV market share. It is followed by Model 3 and Model Y from Tesla. The analysis also indicated that more than 21000 BEVs were registered in Bucharest, the capital of Romania, suggesting that the batteries may have an accelerate urban degradation, due to high-density environment. The technical parameters identified for Spring model are presented in Table 4.

The Spring model has been released in several editions, the best-performing ones being Electric 100 and 65, with LFP and NMC batteries. Thus, the calendar aging model was applied to both chemistries, considering their technical characteristics.

The results for the first scenario, the calendar aging at $T=25^{\circ}\text{C}$, are presented in Figure 2. As it can be observed, the remaining capacity is strongly dependent on SoC. Higher SoC values accelerate calendar aging for both chemistries. NMC degrades faster than LFP due to material differences, exhibiting a capacity loss of almost 17% after the warranty period (2960 days) for a 70% SoC, while LFP, at the same SoC, registered only 11%.

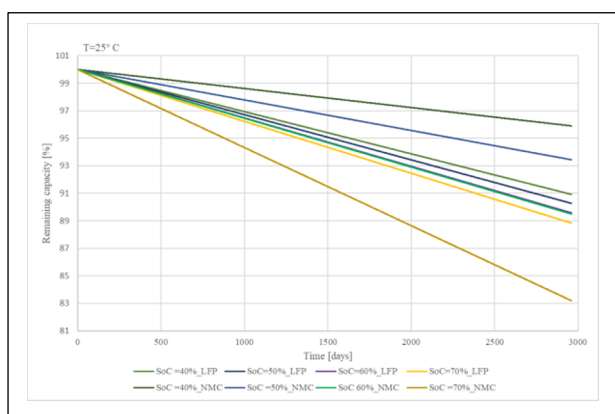


Fig. 2 Remaining capacity of LFP and NMC batteries at $T=25^{\circ}\text{C}$.

An increased temperature severely shortens the battery lifespan. At $T=35^{\circ}\text{C}$, as presented in Figure 3, the capacity fade intensifies. For a SoC of 70%, the remaining capacity of LFP decreases to 80%, while NMC's capacity goes below 60%. The most pronounced degradation for both chemistries is at $T=45^{\circ}\text{C}$, as it can

be seen in Figure 4. LFP remaining capacity falls below 60% for SoC between 50-70%, while NMC's capacity goes under 20% at 60 and 70% SoC. The available capacity of Spring model at the end of primary life varies and it is highly dependent on SoC and T , ranging between 21 to 13.5 kWh for LFP and 21 to under 5 kWh for NMC.

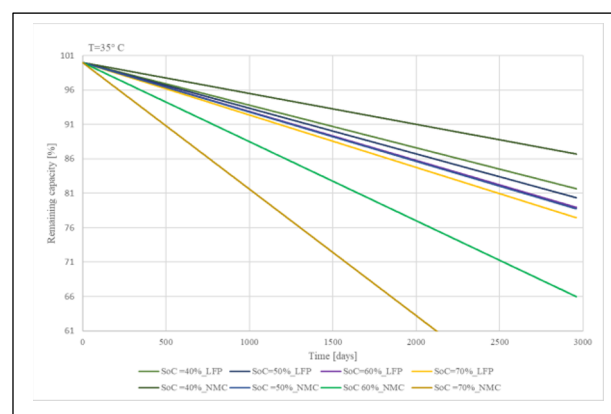


Fig. 3. Remaining capacity of LFP and NMC batteries at $T=35^{\circ}\text{C}$.

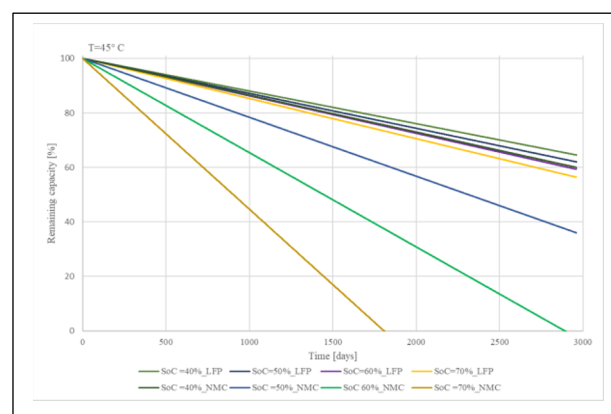


Fig. 4 Remaining capacity of LFP and NMC batteries at $T=45^{\circ}\text{C}$.

4 Conclusions

In this paper, the available capacity of retired LFP and NMC batteries recovered from Dacia Spring model, the most commercialized BEV model in Romania, is

investigated. A calendar aging model is applied considering SoC, operational temperature and time as stress factors. The results show that NMC chemistry is affected more than LFP by the high temperatures and SoC values, indicating that the remaining capacity is expected to be lower than LFPs, decreasing below 40% for 50-70% SoC. In future work the cycling ageing will be analysed to determine the State-of-Health of the retired batteries, in order to separate the ones for second-life applications from the batteries that need to be recycled.

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