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Commentary

Battery passports for promoting electric vehicle resale and repurposing

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Anna Stefanopoulou is the William Clay Ford Professor of Technology at the University of Michigan. She is a fellow of the American Society of Mechanical Engineers (ASME), the Institute of Electrical and Electronics Engineers (IEEE), and the Society of Automotive Engineers (SAE). She has co-authored a book, 22 US patents, and more than 400 publications, eight of which have received awards, on estimation and control of engines, fuel cells, and batteries. She has developed a course in battery controls and is passionate about battery engineering education.

Starting in 2026, most batteries sold in the European Union (EU) will require a battery passport. This initiative is part of a broader legislative framework, led by the European Commission, to improve sustainable battery materials sourcing practices and enable a circular economy. All batteries having a capacity of greater than 2 kilowatt hours (kWhs) will be covered under the legislation, effectively encompassing all electric vehicle (EV) batteries and stationary grid storage batteries.[1,2]

At its core, a battery passport defines a minimum, standard set of information that must be reported for every battery made and sold (see Figure 1). Legislative actions have so far focused on labeling standards enabling raw material traceability and recycling, which has received ongoing support from the European Council and Parliament.[3] However, work remains to finalize the electrochemical performance and durability minimum reporting requirements by 2024, which has been challenging because performance and durability are subject to many different interpretations.

This commentary advocates including a key electrochemical performance indicator as part of the battery passport minimum data reporting requirements: the remaining useful life (RUL). The RUL can be broadly defined as the years, miles, or energy throughput (in kWh) until the battery state of health (SOH) falls below some target minimum:

$$RUL = (years, miles, or\ kWh)\ until\ SOH < SOH_{min}$$

Unlike SOH, which captures the present state of a battery, the RUL is a prediction of the future state of the battery. The RUL may rely on measurements of SOH to provide a forecast of future battery performance. The RUL enables used car buyers, who also earn the least income on average,[4] to make informed purchasing decisions at the point of resale. The RUL also enables repurposers to decide whether it is more economical to recycle a battery or to repurpose it for second-life applications. The RUL is thus a metric at the core of the battery passport's mission to promote battery materials sustainability and equity.

Existing policy discussions concerning battery durability mainly focus on primary use, not secondary use. For example, both the United Nations Global Technical Regulation (GTR)[5] and the California Air Resources Board (CARB)[6] have framed EV durability from the perspective of an 8-year warranty, with no specific provisions for quantifying RUL beyond the first 8 years. Yet, since EVs are expected to be driven for 15 to 20 years and for over 300,000 km,[7] they will likely be resold to used car buyers at least once. Under the existing policy language, a battery

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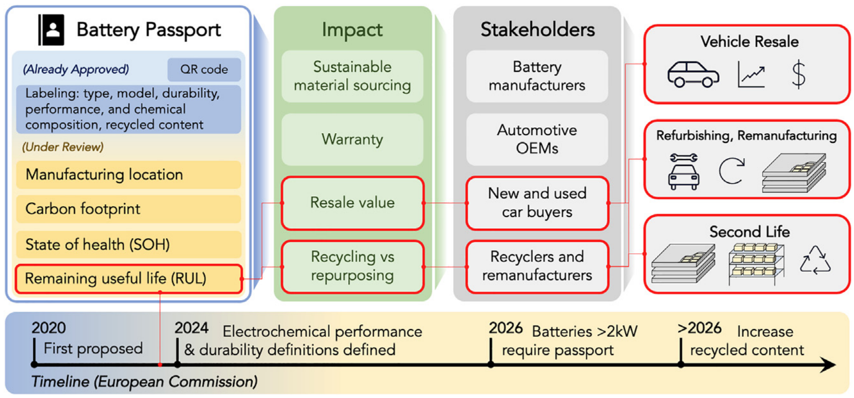

Figure 1. Overview of the digital battery passport concept focusing on applications of the remaining useful life (RUL) metric for electric vehicle resale, recycling, and repurposing

that fails immediately after 8 years will still technically satisfy the 8-year warranty requirement and still be considered "durable." The battery passport directive has an opportunity to address the longevity of batteries beyond 8 years by carefully considering how RUL can be defined and reported as part of the electrochemical and performance indicators to be finalized by 2024.

The importance of RUL has been recognized by the European Commission. A key element of the European legislation is to establish requirements for longevity and performance management. Article 14 specifically mentions that a battery management system (BMS) must contain "data needed to determine the state of health and expected lifetime of batteries." Furthermore, access to the data must be provided to "evaluat[e] the residual value of the battery and capability for further use" and "facilitate[e] the reuse, repurposing or remanufacturing of the battery".[8] In a parallel effort, CARB has also recently implemented state-level legislation requiring the battery SOH to be reported and accurate within five percentage points by 2026.[9] This SOH accuracy requirement, while not directly addressing RUL, acknowledges that SOH monitoring accuracy is necessary for quantifying battery durability.

This commentary highlights the reality that a battery's SOH is not the same as its RUL, and that more discussion around RUL is needed to enable battery reuse and repurposing. We discuss three pitfalls of obtaining a reliable RUL estimate and, in doing so, highlight the reality that RUL accuracy needs to be carefully considered for RUL reporting to be useful. First, we argue that a single-point verification test to obtain SOH cannot, by itself, be used to predict the RUL. Second, we show that 5% SOH accuracy is not enough to make confident RUL predictions. Last, we highlight the need for more physics-based approaches to estimating RUL, especially for repurposing applications where the use case changes.

Single-point SOH measures cannot be used to predict RUL

Let us start with a thought exercise. Suppose that on-board SOH estimates are unavailable, inaccurate, or both. Then, to determine SOH, a battery pack owner is forced to conduct an external capacity check test, i.e., at a hypothetical battery testing station. The measured SOH can then be defined as:

$$SOH_{measured} = \frac{UBE_{measured}\ [Wh]}{UBE_{certified}\ [Wh]} \times 100\%$$

where $UBE_{measured}$ and $UBE_{certified}$ are the measured and certified Useful Battery Energy values as proposed by the UN GTR.[5]

In this example, the single SOH measurement was taken after 8 years of primary use and was measured to be 70%. This measurement suffices for evaluating whether an EV meets warranty requirements according to recent UN GTR[5] and CARB[6] legislation. However, this metric reveals no information about how long the battery will last beyond the 8 years of primary usage. Ultimately, the RUL depends on the underlying aging trajectory that can differ -between battery packs due to differences in cell chemistries, manufacturing processes, and usage conditions.

Figures 2A–2C illustrate three such possible aging trajectories: "linear" (A), "self-limiting" (B), and "accelerating" (C).[10] Defining RUL here as the years from 70% SOH to 50% SOH, we find that the self-limiting trajectory yields an RUL of 16 years, while the accelerating trajectory yields only 1. The self-limiting scenario would thus add the most value in a second-hand electric vehicle market or possibly even be fit for repurposing or second-life applications.

Critically, for all three aging trajectories, the SOH measured after 8 years yields an identical value of 70% SOH, revealing no difference in battery "durability." This example demonstrates that a single-point measurement of SOH, no matter how accurate, is insufficient for predicting RUL. Consequently, battery passports with only a single SOH measurement will have a limited ability to assess RUL. To enable modeling of the aging trajectory, a minimum of three SOH points should be measured and recorded over the life of a battery pack. These SOH points must either be obtained through external testing, i.e., at a battery inspection station, or from the on-board BMS.

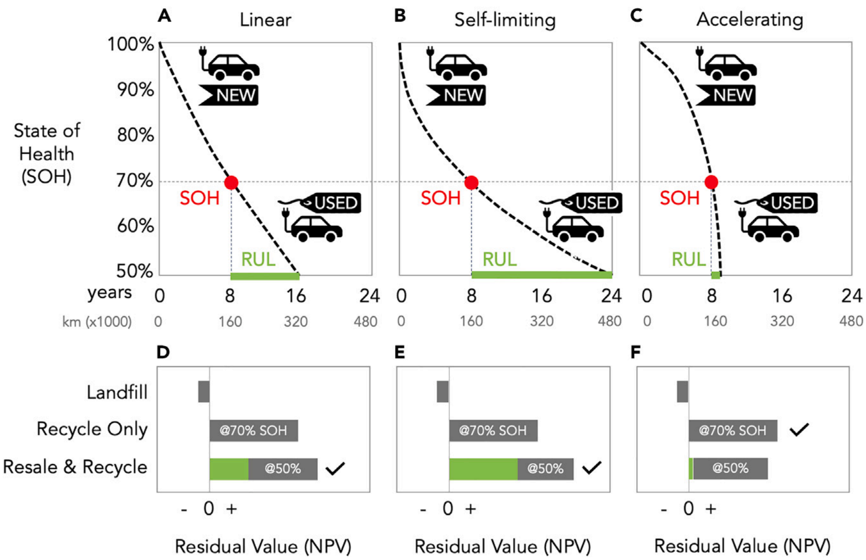

Figure 2. Remaining useful life (RUL) cannot be determined using a single-point SOH measurement

(A–F) Three different aging trajectories are shown: (A) linear, (B) self-limiting, and (C) accelerating. In all three cases, the battery satisfies the warranty of 8 years, 160 km, and 70% SOH (red markers). However, the aging trajectories beyond 8 years differ drastically, affecting the residual value during resale as shown in (D–F). The residual value is quantified by the net present value (NPV), which discounts the future value of recycling.

Figures 2D–2F show how knowledge of RUL can help bolster consumer confidence when deciding between recycling versus reselling an EV battery at the end of its 8-year warranty period. In calculating the residual value of EV resale, we considered both (1) the value from continued usage as an EV throughout its RUL and (2) the value from recycling the spent battery at the end of its RUL. The largest source of uncertainty in this calculation is the RUL. An accurate RUL is thus necessary for facilitating decisions around recycling versus reuse. Similarly, accurate RUL is also necessary for assessing the value of repurposing.

How accurate do SOH estimates need to be for RUL predictions?

Relying on capacity measurements at a service center to establish battery aging trajectories is undesirable because this will require a customer to bring in their pack multiple times throughout the service life, a potentially expensive and time-consuming process. A more economical way to establish an aging trajectory is thus to obtain continuously streaming SOH data from the onboard BMS. However, onboard SOH estimation inaccuracies are unavoidable due to numerous factors including sensor inaccuracy and limited measurement voltage windows.

Intuitively, SOH estimation inaccuracies should also lead to poor RUL prediction inaccuracies. Here, we explore this question more quantitatively using a simple probabilistic model of battery aging trajectories, shown in Figure 3. Since our focus is to study the effect of measurement uncertainty, we employ the simplest possible empirical aging model of the form

$$SOH_{modeled}(t) = a - bt^{c},$$

where a, b, and c are model coefficients and t is the age of the battery in years. Each SOH measurement is sampled from independent normal distributions, each with a standard deviation of 1 percentage point to represent "1% SOH measurement inaccuracy." The model is then fit to the sampled points, which can then be used to extrapolate to 50% SOH. The process is repeated 100 times to generate a distribution of RUL outcomes (gray lines).

The results shown in Figures 3A–3C reveal that the distribution of RUL outcomes depends on the aging trajectory, with the self-limiting aging trajectory having the highest RUL variability and the accelerating aging trajectory having the least. This numerical example shows how SOH estimation inaccuracies manifest as RUL prediction uncertainties.

To further understand how RUL distributions change with SOH inaccuracies, we studied the empirical probability density function of RUL for two different SOH estimation inaccuracy scenarios: 1% inaccuracy (red) and 5% inaccuracy (blue), as shown in Figures 3D–3F. We define the 95% confidence interval (CI) RUL values to correspond to the years at which there is a 95% probability that the true RUL will exceed the given value. With 5% SOH inaccuracy, the 95% CI RUL for all three aging trajectories decreased significantly. For example, for the self-limiting aging trajectory, the 95% CI RUL decreased from 7.2 years to 1.6 years. A 5% SOH inaccuracy thus severely degrades the confidence of RUL predictions.

This example highlights an important fact about consumer confidence: even if a battery pack is technically suitable for resale or repurposing, a consumer will not choose to do so unless they have confidence in the RUL. To achieve this confidence, SOH estimation uncertainty must be sufficiently low.

RUL prediction for repurposing with changing use cases

We finally highlight an inconvenient reality with RUL prediction for battery repurposing: simple, extrapolation-based methods for predicting RUL may

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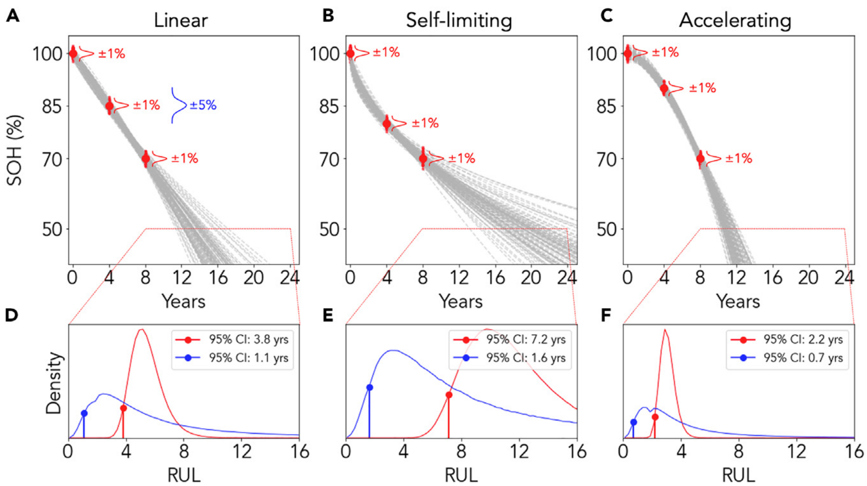

Figure 3. Effect of SOH estimation inaccuracy on estimating the remaining useful life
(A–C) each show 100 aging trajectories (gray lines) modeled using noisy SOH estimates (red markers). Each subpanel represents different ground truth aging trajectories: (A) linear, (B) self-limiting, and (C) accelerating.
(D–F) show the corresponding empirical probability density functions for RUL. The red (blue) curve corresponds to 1% (5%) SOH estimation inaccuracy. The solid vertical lines represent 95% confidence interval (CI) RUL values.

fail to yield accurate RUL predictions for repurposing applications. This issue is unique to repurposing where the battery use case can differ drastically from the primary use case as a traction battery. Figure 4 illustrates this by comparing the battery degradation trajectory in the context of EV resale (A) and repurposing (B). In the case of EV resale, the battery pack continues to be used as a traction battery, and while metrics such as daily mileage may change after resale, the overall battery limits of operation, being bounded by the same BMS, remain the same. The battery aging trajectory is thus expected to be similar during the secondary usage period beyond 8 years.

Comparatively, batteries that are repurposed may be used in completely different contexts compared to the primary usage in EVs, including for home backup power, grid frequency regulation, and low-power electric mobility.[11] For these use cases, the battery degradation rate will tend to be milder than that of the traction battery use case. Extrapolating aging trajectories based on SOH measured during the primary use case may thus underestimate the RUL, leading to a mischaracterization of the battery's longevity in the second-life application.

An accurate assessment of RUL for repurposing therefore requires models that parameterize the degradation rate based on the use case. Simple, extrapolation-based approaches based on past usage history alone cannot achieve this. Rather, more physics-based models[12] may be more appropriate for capturing the dynamics of changing use cases and their impacts battery degradation. Such models typically parameterize battery degradation at the electrode level, whereby environmental factors, such as depth of discharge, temperature, and C-rate, are translated into electrode-level stressors, such as lithium concentration gradients and reaction overpotentials. These physical models can more readily evaluate the impact of repurposing on RUL by dynamically updating the degradation rate as the use case changes. A BMS that implements a physics-based model could, in principle, compute the RUL associated with multiple use cases, enabling consumers to evaluate the suitability of a given battery system for different repurposing applications.

Battery passports and BMSs

The BMS plays a central role in measuring and reporting battery SOH and RUL for each electric vehicle. Existing policy language from the EU and CARB is not prescriptive in how SOH or RUL estimation should be implemented but makes it clear that the BMS is responsible for computing and reporting this information. Here, we briefly discuss some additional considerations relevant to enacting battery passport policies promoting BMS development and RUL estimation.

First, because RUL can be defined at the cell, module, or pack level, battery passport data requirements should carefully weigh the pros and cons of each level of representation. Repurposing applications will generally benefit from module- or even cell-level information because individual units within a single battery pack can exhibit different aging behavior.[13] A remanufacturer with accurate RUL information on individual modules, for example, can then choose which modules to remanufacture and which modules to recycle. On the other hand, for EV resale applications, pack-level RUL information may be sufficient since the pack will not be disassembled. Enabling cell-level RUL will increase BMS sensor and development costs, which must be weighed against the benefit of improving re-manufacturability.

Second, given original equipment manufacturers' (OEMs) general reluctance to publicly share BMS data, policy language around BMS development should focus on RUL accuracy targets and verification methods rather than prescribing implementation details. In this manner, legislators can focus on assuring sustainability end goals while remaining agnostic to technology implementation, thereby respecting

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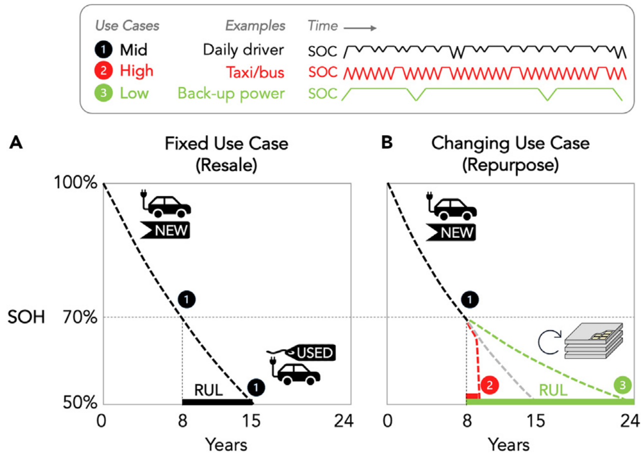

Figure 4. Impact of changing use cases on battery long-term aging trajectory

(A) shows the SOH trajectory before and after EV resale, where the use case remains relatively unchanged.

(B) shows how, in the case of battery repurposing, the SOH trajectory may deviate from the original trajectory due to changing use cases.

the OEMs' needs to protect their technology.

Finally, although the BMS typically only adds 4%–5% to total battery pack costs,[14] this cost does not adequately capture the extra time and engineering effort needed to develop and validate advanced RUL estimation methods. The more complicated the RUL reporting requirements are, the more difficult it will be for OEMs to implement such requirements while remaining competitive in the global EV market. Thus, to encourage widespread adoption of standardized RUL reporting requirements, the requirements themselves should be kept as simple as possible.

Conclusions and recommendations

Battery passport data requirements should be kept as simple as possible. Adopting complex requirements can increase battery costs, slow implementation, and become difficult to enforce. Yet, while existing battery passport data requirements may help maintain minimum performance guarantees for EVs within their first 8 years of use, these same requirements may not enable accurate prediction of RUL beyond 8 years. Without accurate RUL predictions, battery passports can only give limited guidance concerning EV resale and repurposing.

We outlined several key considerations to ensure battery passports can inform EV resale and repurposing decisions. At a minimum, three SOH measurements should be made over different time points to establish an aging trajectory. Each SOH measurement must be sufficiently accurate; a 5% SOH inaccuracy cannot provide confident RUL predictions. Finally, the BMS must enable the accurate prediction of RUL under changing use cases, which may require the adoption of physics-based state estimation algorithms in the BMS. These additional considerations emphasize the need to develop and deploy high-performance BMSs in electric vehicles.

Overall, this commentary raises awareness of the central role that the BMS plays in enabling battery passports to predict RUL. With an accurate BMS, battery passports can help boost consumer confidence in the used EV market. With an accurate, physics-based BMS, repurposers can evaluate second-life application feasibility and fulfill the promise of a circular battery economy.

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DECLARATION OF INTERESTS

A.W. has an affiliation with Tesla that is unrelated to this research. A.S. is an advisory board member for *Joule*. This research reflects work performed at the University of Michigan. All claims expressed in this article are solely those of the authors and do not represent those of their affiliated organizations.

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