Lithium-ion battery lifetime extension: A review of derating methods

Haijun Ruan[a*], Jorge Varela Barreras[b], Timothy Engstrom[c], Yu Merla[c], Robert Millar[c] and Billy Wu[a,d*]

[a] Dyson School of Design Engineering, Imperial College London, SW7 2AZ, UK.
[b] Department of Civil and Environmental Engineering, Imperial College London, SW7 2AZ, UK
[c] Williams Advanced Engineering, Grove, OX12 0DQ, UK
[d] The Faraday Institution, Quad One, Harwell Science and Innovation Campus, Didcot, UK

Abstract

Extending lithium-ion battery lifetime is essential for mainstream uptake of electric vehicles. However, battery degradation is complex and involves coupling of underpinning electrochemical, thermal and mechanical processes, with behaviours varying based on chemistry, operating conditions and design. Derating is an attractive approach for extending lifetime due to ease of implementation, however, uncertainties remain around the optimal approach and their impacts. In this paper, we present a critical review of derating methods; dividing approaches into dynamic or static approaches based on whether the derated parameters changed with battery aging or not. Furthermore, we analyse and comment on approaches which are classified as being either heuristic or model-based. Analysis, comparison, and discussion around the derating sub-categories are presented towards highlighting underpinning insights of derating. Benefits and impacts of derating are quantified, and challenges with implementation are identified along with identification of research gaps, practical considerations and perspectives for future directions.

***Keywords**:* Lithium-ion battery, lifetime extension, derating, degradation, lithium plating, charging

* Corresponding author. E-mail: h.ruan@imperial.ac.uk; billy.wu@imperial.ac.uk

1. Introduction

To achieve a net-zero carbon future, electric vehicles and grid-scale energy storage systems are needed; driving the rapid scale-up of lithium-ion batteries. Since the battery is one of the most expensive components[1,2], extending its lifetime is critical. Derating is one approach for lifetime extension and refers to operation of a device at less than its maximum capability to ensure safety, reduce degradation, or avoid system shutdown[3,4] (Fig. 1). This is attractive since it can be implemented at minimal cost and does not influence system reliability or generate additional safety issues[3-5].

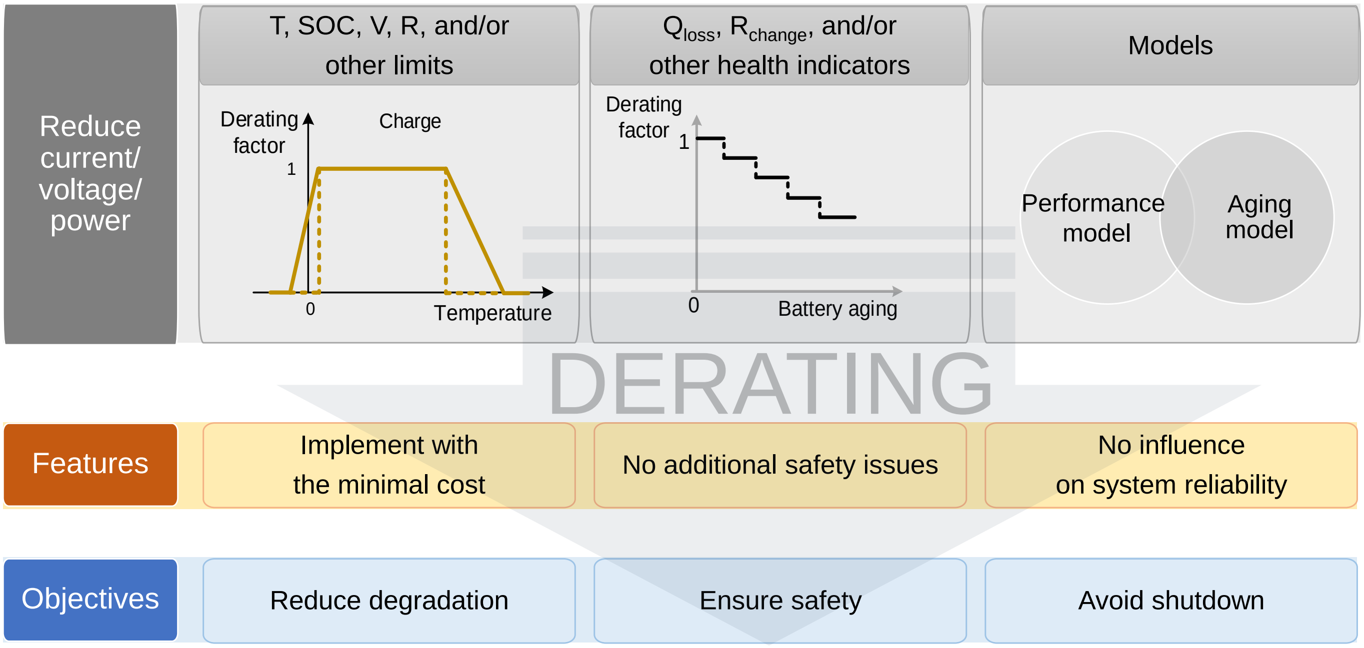


Fig. 1. Derating control: its fundamental operation modes, features, and objectives. T: Temperature; SOC: State of charge; V: Voltage; R: Resistance; Q_{loss}: Capacity loss; R_{change}: Resistance change.

Battery degradation is a complicated problem involving electrochemical, thermal and mechanical processes, with these being highly dependent on the operational conditions[6,7,8]. For example, high temperature exposure leads to the growth of solid electrolyte interphase (SEI) and low-temperature charging often triggers lithium (Li) plating on the anode[9,10]. Usage at high state-of-charge (SOC) induces instability of the cathode and high current rate (C-rate) operation, often results in particle cracking[9,11]. Furthermore, different battery chemistries can result in varied behaviours. For instance, the SEI forms and grows in graphite (Gr) anodes but there is often no SEI formation in lithium titanium oxide (LTO) anodes[12]. In addition, battery design (e.g. power vs energy) also influences the degradation, with an example being power orientated batteries being able to withstand a high C-rate with less particle cracking due to more homogeneous electrode use compared to energy focused cells[13,14,15].

The complexity of battery degradation poses a significant challenge when developing optimal derating approaches. Avoiding battery operation at extreme temperatures and high SOC with high C-rates is one basic derating approach (Fig. 1), which would extend battery lifetime and prevent safety issues[4-6]. However, decreasing the operational range, limits available energy and power, and thus it is important to make a good balance between battery lifetime and performance.

A key consideration for optimal derating control is awareness of battery states, such as state-of-health (SOH). For fresh cells, a battery can generally withstand higher current loads, however as the battery ages, the same current may lead to accelerated degradation. For example, a battery may be charged at a specific current without issue at beginning-of-life, but as the battery ages, effects such as active material loss and resistance increase, means that the same charging current can potentially lead to lithium plating[16]. Therefore, it is critical to modulate the operating parameters as the battery ages (e.g. the derating factor reduces with battery aging as shown in Fig. 1).

Although derating is imperative to extend battery lifetime, limited studies have thoroughly investigated this[3-5] and there are limited reviews relevant to this topic, with existing reviews only briefly covering this topic; without comprehensive review. A list of existing review papers and their relevance to lithium-ion battery derating, is shown in Table 1 for the convenience of the reader. Consequently, we attempt to fill this gap, with a critical review that aims to classify existing derating methods, quantify their benefits and allude to underpinning rational for performance improvement. From this, research gaps are identified, along with industry considerations and future directions.

Table 1 Notable existing review articles that are relevant to lithium-ion battery derating.

References	Topic	Relevance to derating
Barreras et al. (2018)[3]	Reviewed common derating strategies for lithium-ion batteries	Reviewed the temperature, SOC, and voltage-based derating approaches
Woody et al. (2020)[6]	Reviewed strategies to limit battery degradation and provide guidance for stakeholders	Provided guidance about the temperature, SOC, and voltage-based derating approaches
Wassiliadis, et al. (2021)[17]	Reviewed fast charging strategies for lithium-ion batteries	Mentioned several fast charging papers about SOH-based derating (capacity loss and/or resistance increase-based)

The remaining part of this paper is organized as follows. Battery derating is categorized in Section 2, with the following Section 3 and Section 4 presenting and analysing static and dynamic derating methods, respectively. Section 5 explores derating considerations in industry with perspectives and future direction discussed in Section 6, followed by conclusions in Section 7.

2. Battery derating and its categorisation

2.1 Battery derating considerations

Derating is an intentional process to limit operating windows to reduce stress factors in order to extend device lifetime, however, a fine balance needs to be made in order not to overly derate; reducing performance. The optimum choice of parameters thus needs consideration of the underpinning mechanisms of degradation, cell design and operating conditions.

The operating SOC, as an example, is one key stress factor in battery lifetime, with degradation limits varying with battery types. For instance, low SOC cycling generally resulting in a slow degradation in nickel manganese cobalt oxide (NMC)/Gr cells[18] contrasted with a serious deterioration for NMC/Gr-silicon batteries[19]. This difference in behaviour can be attributed to the non-linear current distribution in composite anodes driven by the different open circuit voltage (OCV) profiles of the Gr and silicon[15]. Therefore, no unified derating method exists for all battery types; with the optimal derating approach needed to be carefully examined and adapted for each battery chemistry, design and application.

In order to quantify the impacts of derating approaches reported in the literature, we introduce the derating factor which quantifies the reduction of investigated variables. This can be expressed as:

$$\delta_{\mathrm{derate}} = \frac{\chi_{derate}}{\chi_{initial}}, \qquad \chi = I,\ V,\ P \tag{1}$$

where χ_{derate} and χ_{initial} represents the derated and initial parameters (I = current, V = voltage, and P = power), respectively. Initially, a battery has a derating factor of 1, while 0 represents a completely derated state.

When analysing charging cases, the derating factor can also be estimated from the charging time, expressed as

$$\delta_{\mathrm{derate}} = \frac{t_{initial}}{t_{derate}} \tag{2}$$

where t_{derate} and t_{initial} represent the charging time using the derating and regular methods, respectively.

In order to quantify the benefits of derating, we analyse the increased number of cycles at end-of-life. Compared with the regular method (reference), this can be expressed as:

$$L_{\mathrm{cyc}} = \frac{Y_{derate,\mathrm{cyc}} - Y_{ref,cyc}}{Y_{ref,cyc}} \tag{3}$$

where $Y_{\mathrm{derate,cyc}}$ and $Y_{\mathrm{ref,cyc}}$ represent the (full) cycles achieved till capacity has decreased by 20% using the derating and regular methods, respectively.

In some studies, the batteries did not reach end-of-life and thus we calculate the rate of aging to quantify the lifetime extension. This can be described as:

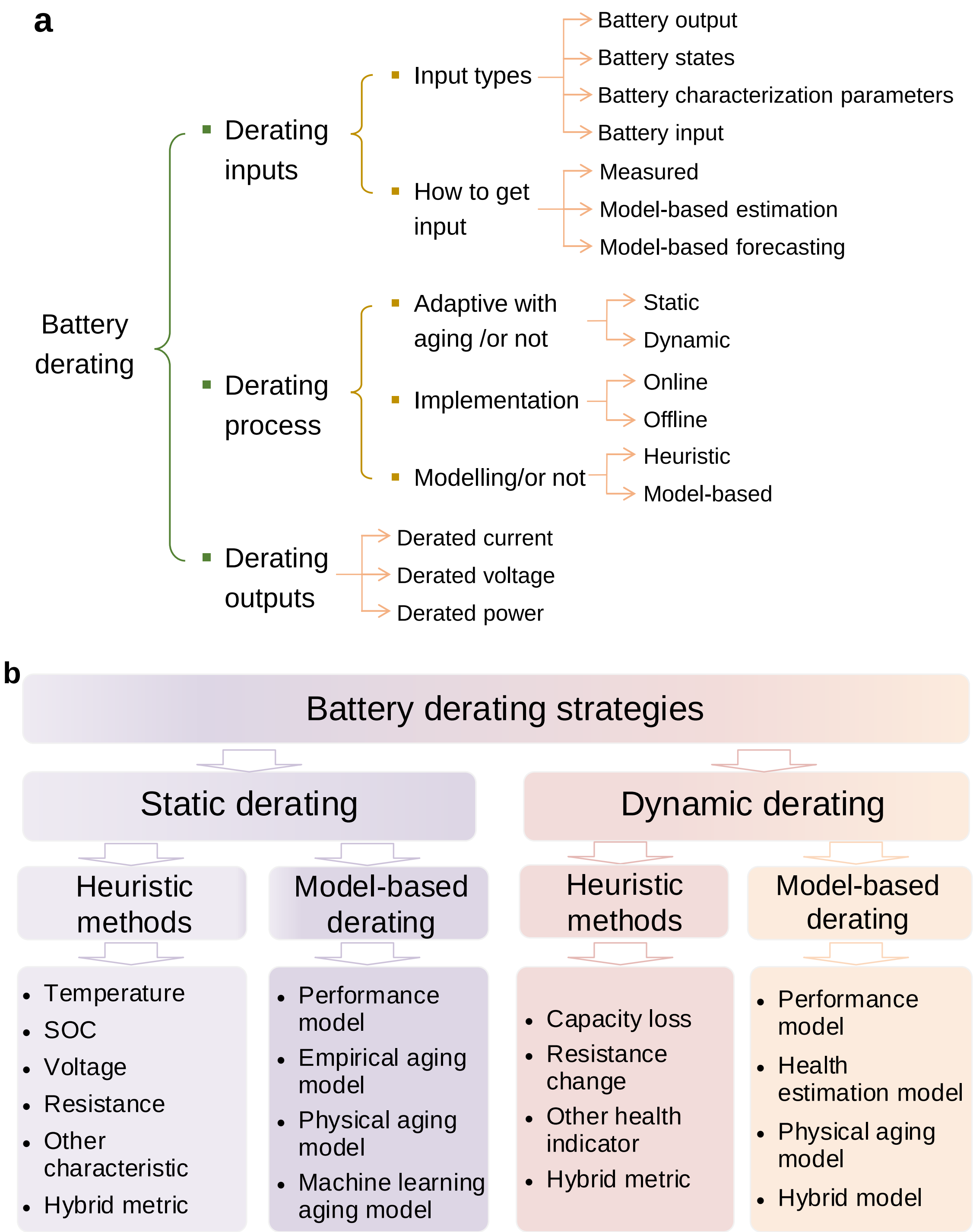
$$L_{\mathrm{Q}} = \frac{Y_{ref,\mathrm{Q}loss} - Y_{derate,\mathrm{Q}loss}}{Y_{ref,\mathrm{Q}loss}} \quad (4)$$

where $Y_{\mathrm{derate,Qloss}}$ and $Y_{\mathrm{ref,Qloss}}$ represent the rate of capacity loss using the derating and regular methods, respectively, with units of %/cycle.

2.2 Battery derating categorisation

Battery derating can be categorised by considering: inputs, processes, and outputs of the derating control (Fig. 2a). For example, inputs can be: measurable states such as voltage, temperature or resistance, and estimated states, such as SOC, SOH or anode potential (see detailed classification in Supplementary Fig. S1); in processes, the derated parameters can be adaptively changed with aging or not, corresponding to the dynamic or static derating (Fig. 2b); for outputs, this can be classified as current/voltage/power-based derating methods (Supplementary Fig. S1d). As the current is easy to control, most of the existing methods use current derating.

Battery static and dynamic derating are classified by whether the derated parameters remain static or change with battery age, respectively (Fig. 2b). Static and dynamic derating can be further divided into heuristic and model-based approaches. We classify model-free approaches as heuristic derating, which is generally formulated through experimental degradation analysis and/or strategies derived from prior experiences (often informed by review of the literature), whereas model-based derating requires the use of a model, such as empirical, physical-based, or machine learning (ML) based.


a
Battery derating
Derating inputs
Input types
Battery output
Battery states
Battery characterization parameters
Battery input
How to get input
Measured
Model-based estimation
Model-based forecasting
Derating process
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Static
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Implementation
Online
Offline
Modelling/or not
Heuristic
Model-based
Derating outputs
Derated current
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Battery derating strategies
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Dynamic derating
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Model-based derating
Heuristic methods
Model-based derating
Temperature
SOC
Voltage
Resistance
Other characteristic
Hybrid metric
Performance model
Empirical aging model
Physical aging model
Machine learning aging model
Capacity loss
Resistance change
Other health indicator
Hybrid metric
Performance model
Health estimation model
Physical aging model
Hybrid model

Fig. 2. Battery derating categorization. a. Potential classifications of derating methods considering the inputs, outputs and processes (see further classification in Supplementary Fig. S1). b. Detailed derating classification considering the derated parameters adaptively changed with aging or not.

Based on these definitions, Table 2 analyses these approaches based on literature works. Almost all the aging model-based derating methods have not been experimentally validated, while most of the dynamic derating methods were experimentally tested and explored the extension of battery lifetime. An extensive number of works investigated the effects of temperature, SOC range, and voltage, on battery degradation. For example, Wikner et al.[22] investigated the degradation of batteries under different SOC ranges and presented an empirical aging model to calculate the lifetime extension under different types of driving with small depth-of-discharge (DOD). Their simulation results indicated that charging the battery to 50% SOC after each trip rather than fully charging can increase battery lifetime by 44-130%.

Table 2 Summary of derating references. Several representative references for aging investigation are included for derating analysis as there is almost no paper directly presenting derating control.

Derating method		Battery type	Experiments/simulation /analysis	Lifetime comparison	References
Static derating	Temperature	NCA/Gr	Experiments	No	Patnaik et al.[20]
		LFP/Gr	Simulation (Aging analysis)	Yes	Liang et al.[21]
	SOC	NMC-LMO/Gr	Experiments/simulation	Yes	Wikner et al.[22]
		NMC622/Gr	Experiments (Aging analysis)	Yes	Gauthier et al.[18]
	Voltage	LCO/Gr	Experiments (Aging analysis)	Yes	Gao et al.[23]
		NCA/Gr	Experiments (Aging analysis)	Yes	Li et al.[24]
	Resistance	NMC/Gr	Experiments	No	Ahn et al.[25]
		NCA/Gr	Experiments	Yes	Sebastian et al. [26]
	Other characteristic	NCM532/Gr	Experiments	No	Rodrigues et al. [27]
		NMC/Gr	Experiments	Yes	Spingler et al.[28]
	Hybrid metric	NMC811/Gr	Experiments	Yes	Liu et al.[29]
	Performance model	NMC/Gr	Simulation	No	Remmlinger et al.[30]
		Gr	Simulation	No	Iqbal et al.[31]
	Empirical aging model	LFP/Gr	Simulation	Yes	Schimpe et al.[7]
		LFP/Gr	Simulation	Yes	Sowe et al.[32]
	Physical aging model	NMC/Gr	Experiments	Yes	Yin et al.[33]
	ML aging model	65Ah battery pack	Simulation	Yes	Bibinsha et al.[34]
Dynamic derating	Capacity loss	NMC622/Gr	Experiments	Yes	Epding, et al.[35]
		NMC/Gr	Experiments	Yes	Keil, et al.[36]
		NCA/Gr	Experiments	Yes	Koleti, et al.[37]

	51Ah high-energy pouch cell	Experiments	Yes	Sieg, et al.[38]
Resistance change	NCA/Gr	Experiments	Yes	Koleti, et al.[39]
Other aging indicator	NCA/Gr	Experiments	Yes	Koleti, et al.[37]
Hybrid metric	51Ah high-energy pouch cell	Experiments	Yes	Sieg, et al.[34]
Performance model	LCO-NMC/Gr	Experiments	Yes	Guo et al.[40]
Health estimation	Sanyo UR14500P	Experiments	Yes	Lee et al.[41]
Physical aging model		Simulation	Yes	Mandli et al.[42]
Hybrid model	LFP/Gr	Simulation	Yes	Su et al.[43]

Gr: Graphite; NCA: Nickel-cobalt-aluminium oxide; LFP: Lithium iron phosphate; LMO: lithium ion manganese oxide; LCO: Lithium cobalt oxide;

3. Static derating

Static derating involves limiting the battery performance based on derated parameters that do not change as the battery ages. Here, the battery current/voltage during charging/discharging are reduced to prevent operation outside certain operating regimes, bounded by static temperature, SOC, voltage, resistance or other constraints. These static derating approaches can be divided into heuristic or model-based derating methods.

3.1 Heuristic methods

Heuristic methods refer to derating control defined by degradation experiments and analysis or qualitative understanding of battery degradation and safety characteristics. Here, once a high aging stress is measured, the current (or voltage/power) will be reduced. Fig. 3a illustrates four common heuristic derating methods, corresponding to four aging stress variables: operating temperature, SOC, voltage and battery resistance, and other characteristic-based derating, such as the anode potential, as well as hybrid metric-based derating, which considers several aging stress factors.

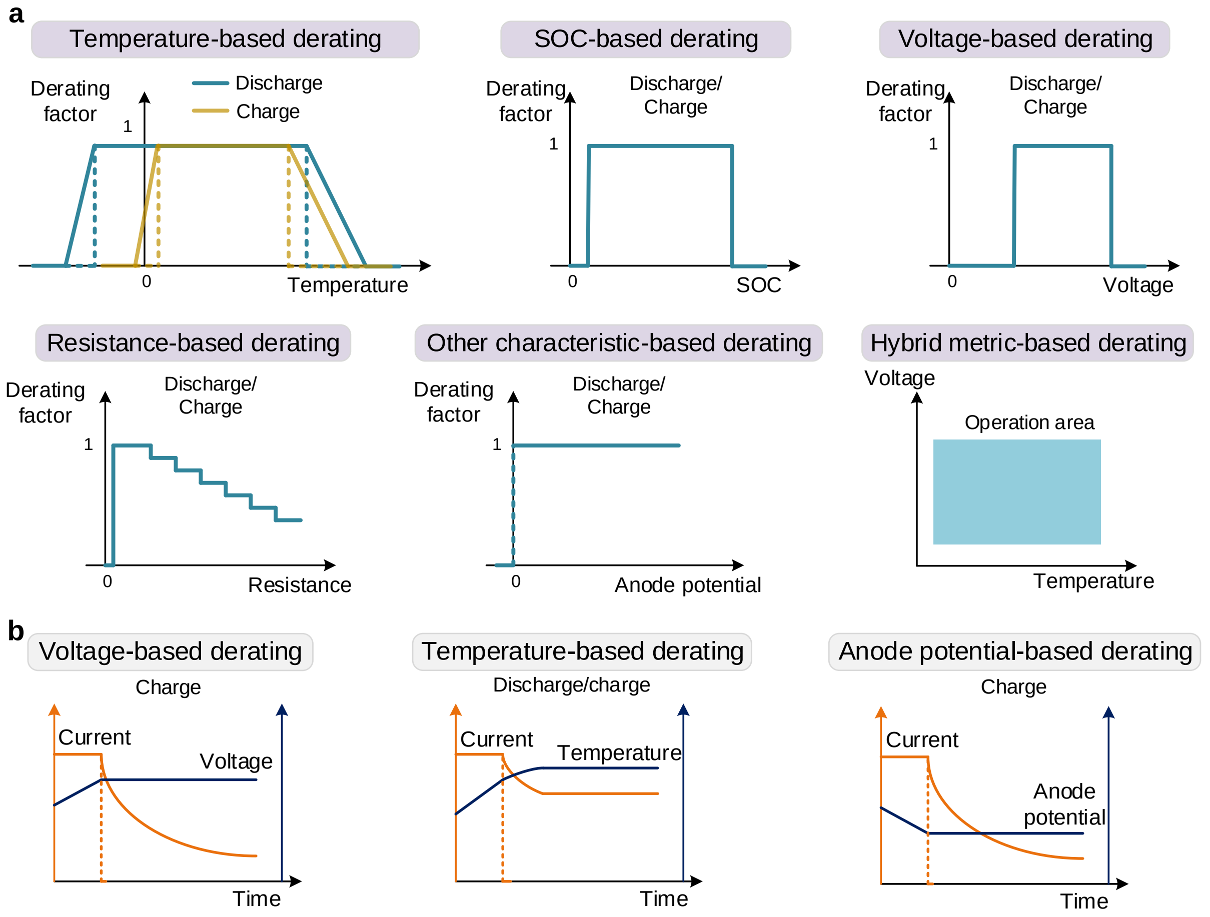


Fig. 3. Heuristic static derating methods. a. Illustration of temperature, SOC, voltage, resistance, other characteristic and hybrid metric based methods. b. Possible current change profiles in the voltage, temperature and anode potential based derating methods.

3.1.1 Temperature-based derating

Both high and low temperature operation generally accelerates battery degradation, due to fast SEI growth and Li deposition, respectively, with operation at near room temperature facilitating a long-life battery[44,45,46]. Based on these broad relationships, the derating factor at moderate temperatures is usually 1, representing unrestricted operation, but at increasing extreme temperatures, derating is advised (Fig. 3a). In general, the allowable temperature range for charging is narrower than that for discharging[46], with an example of charging at sub-zero temperatures unpermitted with suggested current due to sluggish kinetics and slow transport in the battery which can lead to Li plating[47]. However, discharging at sub-zero temperatures, such as at -20°C[48,49], is often allowed since Li plating does not occur during discharge.

To achieve a good balance between performance and lifetime, constant temperature (CT) control can be adopted. Patnaik et al.[20] developed a CC-CT-CV charging method with battery temperature limited at a pre-set point by modulating the charging current, as shown in Fig. 3b (CC = Constant current, CV = Constant voltage). This derating control attempts to maximise the charging performance while limiting the battery temperature to avoid accelerated SEI growth. However, the limiting temperature (~30˚C)[20] in this work is modest, and an optimised approach for determining the objective temperature remains an open question.

3.1.2 SOC-based derating

Rapid charging at high SOCs is often not suggested as the likelihood of Li deposition increases[50,51]. Furthermore, operation at high SOC is in a regime where the cathode is more delithated, making the structure unstable and possibly leading to particle fracture[18,2255] in addition to the high voltages which promotes electrolyte oxidation[54]. Angenendt et al.[52] limited the operation of batteries at high SOCs, and their simulations indicated that low average SOC operation increased battery lifetime by ~100% (~4.3 years). Conversely, low SOC operation is also not recommended because in most cases the increased resistance leads to more heat generation, which may result in increased SEI growth. Zhu et al.[44], for instance, showed that the ohmic resistance and SEI resistance increased significantly following sudden capacity fade when cycled at low SOC ranges. Furthermore, for Gr-silicon composite anodes, rapid silicon degradation is observed during cycling between 0-30% SOC[19], which is primarily attributed to the high current density in the silicon material due to low the non-linear current splitting between the two active material phases driven by OCV differences[14].

Table 3 Summary of the representative studies about battery SOC dependent degradation.

	Which SOCs are better for long lifetime	Battery	Cycling conditions	Possible aging mechanisms	references
1	Without low SOC (e.g. 5%)	NMC532-NCA/Gr	1C cycling at 25 °C; different DOD: 20%, 40%, 60% with different mean SOC	SEI growth	Zhu J. et al.[53]
2	A lower DOD (e.g. 50%)	NMC622/Gr	1/10C, C/5, C/3 cycling at 40 °C	LLI: SEI formation and growth, and LAM_{PE}	Gauthier R. et al.[22]
3	20-80%	8Ah pouch NMC/Gr	6C cycling at 25 °C; DOD: 20%	LLI	Gao Y. et al.[54]
4	Low mean SOC (e.g. 30%) and small SOC range (e.g. 20%)	LCO/Gr	C/2 charge, 2C or C/2 discharge at 25 °C;		Saxena S. et al.[55]
5	Medium SOC range (e.g. 20-80%)	LFP/Gr	1C discharge, 0.5C charge at 25 °C; 20% DOD		Jiang J. et al.[56]
6	Restricted SOC range (e.g. 10-70%)	Cylindrical 0.4Ah NCA /Gr	1C cycling at 25 °C and 60 °C; SOC: 10-70%, 0-100%	NCA particle cracks and film layer formed and grown	Watanabe et al.[57]
7	Low dependency on SOC range (40-60% better)	LFP/Gr	0.5C charge, 1C/2C/3C discharge, at 25 °C/ 15 °C/ 35°C		Preger et al.[58]
	20-80%	NMC/Gr		The metal oxide cathodes' higher operating voltages promote electrolyte oxidation	
	20-80% (40-60% the best)	NCA /Gr	0.5C charge, 1C/2C discharge, at 25 °C/ 15 °C/ 35°C;		
8	Low dependency on SOC range at 45 °C; 37.5-67.5% SOC at 0/20 °C;	Sony US18650V3 NMC/Gr	1C charge, 1C/2C discharge, at 45 °C/ 20 °C/ 0°C;Different DOD and mean SOC	Gr electrode volume changes; undesirable reactions and thickening SEI at high SOCs	Maheshwari et al.[59]
9	47.5-52.5% (20-80% also good)	26650 LFP/Gr	1C/2C/3.5C cycling at 30°C; Different DOD, 50% mean SOC		Wang et al.[60]
10	Narrowed SOC, e.g. 10-90%	Cylindrical 3Ah NCA /Gr	0.1C charge, 1C discharge, at 30 °C; Different DOD and mean SOC	SEI growth and LAM	Zhang et al.[61]
11	25-75% at 25/35 °C; 32.5-67.5% at 45 °C	NMC/Gr	C/3, 1C, 2C charge, C/3, 1C, 2C discharge, at 25, 35, 45 °C		Hoog et al.[62]
12	40-60%	UR18650E NCA/Gr	1C cycling at 35°C	Cells cycling crossing a transition between anode voltage plateaus show faster aging due to mechanical stresses.	Ecker et al.[63]
13	25-75%	Cylindrical 8 Ah LFP/Gr	1C cycling at 40°C		Lewerenz et al.[64]
14	DOD<50%	NMC-LCO/LTO	3C cycling at 45°C	Cathode degradation	Chahbaz et al.[65]
15	Avoid using 0-30% SOC at 25, 45 °C	NMC811/Gr-Silicon	0.3C charge, 1C discharge, at 10, 25, 45 °C	LAM_{NE-Si}	Kirkaldy N. et al.[19]
16	Avoid the operation in the high SOC (e.g. >60%)	NMC-LMO/Gr	1C, 2C, 4C cycling at 25, 35, and 45 °C	LAM_{PE}; LLI: side reactions, such as, SEI growth	Wikner et al.[66]

LLI: Loss of lithium inventory; LAM_{PE}: Loss of active material in the positive electrode; LAM_{NE}: Loss of active material in the negative electrode; LTO: Lithium titanate oxide

Operation at moderate SOC ranges is thus preferred, supported by most studies presented in Table 3, with the ideal SOC range being different for different battery chemistries/types. For example, Hoog et al.[62] suggested that a SOC range of 25-75% is better for their NMC/Gr batteries at 35°C, while Ecker et al.[63] showed that operation at the same SOC range leads to the fast capacity decrease for their nickel-cobalt-aluminium oxide (NCA)/Gr batteries and a SOC range between 40-60% is ideal. Furthermore, the appropriate SOC range may change with the operating conditions. For example, Kirkaldy et al.[19] suggested that operating between the 0-30% SOC range induces the rapid loss of silicon material at 25°C and 45°C, leading to fast capacity fade of NMC/Gr-silicon batteries, however, the degradation at 10°C is slow. This is likely because at low temperatures, large overpotentials on the silicon cause the Gr to take on a larger portion of the charge throughput.

Beyond this behaviour, it should also be noted that for some batteries, the degradation may show low dependency on the SOC range but relates highly to the DOD[58,65,67]. Preger et al.[58] showed that the lifetime of their lithium iron phosphate (LFP) batteries is almost independent of the SOC range, likely attributed to the stable LFP electrode and less electrolyte oxidation due to the relatively low cathode voltage. Chahbaz et al.[65] pointed out that an operating DOD below 50% is better for the NMC-LCO/LTO (LCO = Lithium cobalt oxide, LTO = Lithium titanate oxide) batteries, whatever the mean SOC is. Furthermore, for some batteries, low-SOC cycling does not accelerate the degradation. Wikner et al.[22,66], for instance, illustrated that their NMC-LMO/Gr (LMO = lithium manganese oxide) battery exhibited slower degradation during cycling between 0-30% SOC than other SOC ranges. This is likely attributed to the high cathode degradation possibly due to Mn dissolution[68], and particle cracking stemming from the mechanical instability and structural changes in the NMC material[69], and high loss of lithium inventory (LLI) due to the increased side reactions, such as electrolyte oxidation and SEI growth, at high SOC ranges. Therefore, there is no specific SOC range suitable for all batteries, and for each battery, the appropriate operating range should be explored by experiments/simulations.

3.1.3 Voltage-based derating

The upper and lower cut-off voltages are imposed to avoid damage to the battery but this also has a strong link to the energy density of a cell and its lifetime. In the case of the upper cut-off voltage, lowering this extends lifetime but reduces the available energy[24,70]. For example, Su et al.[71] compared the lifetime of batteries when charging to 4.1 V and 4.2 V and showed that charging to 4.1 V leads to a lower aging rate, due to the decreased electrolyte oxidation caused by the high voltage of the positive electrode. The impact of varying the lower cut-off voltage seems to have varied influence on battery lifetime, especially for different battery materials. Choi et al.[72] investigated the degradation of LCO/Gr batteries with the discharge cut-off voltages ranging from 2.75-3.55V, with no noticeable dependence in the rate of capacity loss shown with different cut-off voltages within 500 cycles. Meanwhile, Li et al.[24] illustrated that increasing lower cut-off voltage results in a low capacity loss for their NCA battery, which they primarily attributed to the decreased loss of active material in the positive electrode (LAM_{PE}) due to the shallow lithiation of the NCA cathode. Bazlen et al.[73] compared aging behaviours of Gr-silicon composite batteries with lower cut-off voltages of 2.5 V and 3.1 V, and concluded that limiting the lower voltage increases the stability of silicon as the silicon is never completely delithiated.

CV control is often used to fully (de)lithiate electrodes without violating voltage limits, with the charging current gradually decreasing as shown in Fig. 3b. Here, as the CV hold voltage decreases this usually leads to a slow degradation [23,72]. For instance, Gao et al.[23] showed that a CV hold at 4.1 V enhances the lifetime of a cell, with 4.2 V CV hold driving the cathode to a high voltage; making it structurally unstable, leading to the loss of lithiated cathode material.

3.1.4 Resistance-based derating

Battery resistance varies with battery SOC, temperature, applied current and age[74,75,76]. In the resistance based derating approach, the current is change based on its resistance[25,77,78], thus minimising the heat generation and increasing efficiency. To enhance charging efficiency, Ahn et al.[25] proposed a resistance adaptive charging method, where higher currents were used for low resistance regions, with lower currents being used for the high resistance regions. Compared with a conventional CC charging strategy, the total charging losses of both the battery and charger losses were decreased by above 7.2%. Jiang et al.[79] also illustrated that the resistance-based derating method can decrease battery energy loss by 1.2% compared with the traditional charging approaches. Instead of fine tuning charging current with battery resistance, Sebastian et al.[26] proposed a resistance-based two-stage CC charging method, which firstly used 1C charging until the resistance becomes quite low (~40% SOC) and then applied 2C charging. At the expense of a charging time decrease of ~12%, this method extended battery lifetime by 44% likely due to the low temperature rise compared with the 2C charging, and low mechanical stress at the low SOCs.

3.1.5 Other characteristic-based derating

Beyond the aforementioned approaches, other characteristic states, such as anode potential (Fig. 3b), can be used to derate performance. For instance, Liu et al.[29] implanted a reference electrode into a cell to provide anode potential measurements and modulated the charging current, which is similar to that in Fig. 3b, to maintain the anode potential within safe regions to avoid Li plating. However, approaches such this rely on having reliable measurements has highlighted by Rodrigues et al.[27]. Here, they investigated the errors in anode potential measurements which are intrinsic to reference electrodes, and determined the maximum charging rate at which lithium deposition can be mitigated while achieving the fastest charging. However, whilst the anode potential information is powerful in avoiding Li plating but implementation in real world applications is challenging.

Various approaches to infer the onset of Li plating have thus been explored. Spingler et al.[28] explored the link between local volume expansion measured by laser triangulation and Li plating on Gr anode, as the deposited lithium causes a higher volume change of batteries than the intercalated lithium[80]. They thus presented a fast charging protocol which enabled both 11% charging time reduction and 16% reduction of capacity loss per cycle as compared to 1C CCCV charging.

3.1.6 Hybrid metric-based derating

Instead of considering one static limit, we can employ several restraints to regulate charge/discharge. For example, Ouyang et al.[81] explored the degradation of LFP batteries under different C-rates and cut-off voltages at low temperatures and concluded that the charging current should be reduced to below 0.25C at -10 °C while the charging cut-off voltage should be lower than 3.55V to prevent accelerated degradation. Liu et al.[29] showed a high temperature increase, reaching near 60 °C, when using the anode potential-based charging method, and presented a charging method where the current is derated with the limitation of both anode potential and battery temperature, which reduces charging time by approximately one half while maintaining the similar degradation compared with the fast charging strategy recommended by the manufacturer.

3.2 Model-based derating

Instead of developing derating approaches simply based on the experimental tests, model-based derating methods are informed by a model, which estimates battery states or compares aging stress variables (Fig. 4). Current (or voltage/power) modulation may, therefore, be based on the temperature, SOC, voltage, resistance or other metrics.

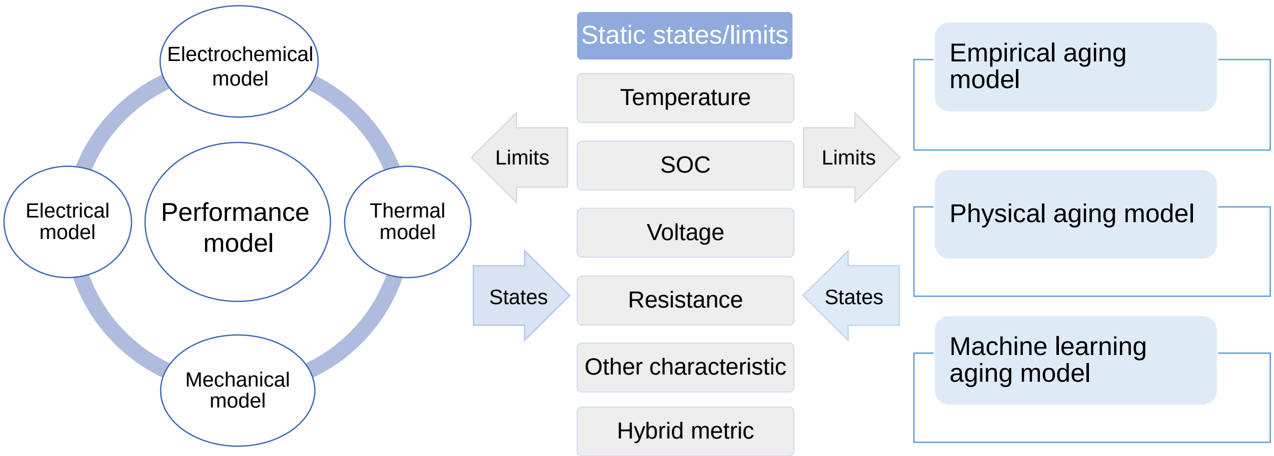


Fig. 4. Model-based static derating methods

3.2.1 Performance model-based derating

A performance model, such as an equivalent circuit, electrochemical and/or thermal model, captures the information on the voltage, anode potential, or temperature of a battery, and can thus be used to regulate the charge/discharge processes[82,83]. Ye et al.[84] used lumped electrical and thermal models to optimize the charging current that aimed to reduce both the charging time and temperature increase, which enabled a decrease in the charging time and temperature rise by 9.5% and 17.9% at 40 °C, respectively, compared with traditional CCCV methods.

Physic-based performance models generally provide information on internal battery states, such as the anode potential, and particle stress, and thus can offer more in-depth information. Examples of their use in derating includes Remmlinger et al.[30], who used a reduced-order electrochemical model with the aim of keeping the anode potential positive during charging to prevent Li plating. Iqbal et al.[31] implemented a coupled electrochemical-mechanical model to evaluate the stress levels inside battery particles and proposed a stress-regulated pulse charging protocols, to achieve a fast charging with minimal mechanical fracture of the active material.

In order to implement the anode potential based derating, Chu et al.[85] constructed an anode over-potential observer based on a reduced-order electrochemical model. Considering the complexity of the electrochemical model, Lu et al.[86] presented a decomposed electrode electrical model by inserting a reference electrode to observe anode potential under dynamical operation conditions. These anode potential based derating approaches were experimentally validated using the specific batteries without noticeable Li plating[85-87], but how to economically apply this method in a battery pack remains a gap.

3.2.2 Empirical aging model-based derating

With a comprehensive experimental aging data set, Schimpe et al. presented a semi-empirical model to describe battery degradation under various conditions[39] and then developed a degradation-aware current derating method[5]. The degradation model is used offline to predetermine the degradation rate, which informs how the current is modulated to achieve the target lifetime. This considers both SOC and temperature effects and has been shown to enable a lifetime extension of 65%. Sowe et al.[32] used the same semi-empirical aging model to present a SOC-based derating method and concluded that the model-informed approach increased battery lifetime by up to 45% (7 years) compared to traditional methods. Hoke et al.[88] adopted National Renewable Energy Lab's semi-empirical aging model[89,90] and presented a charging method that used a prediction of the next day's vehicle usage to charge the battery only as needed. This approach extended battery useable life by up to 150% over traditional charging due to minimizing time spent at high SOC. However, whilst these results are promising these models do not capture all degradation modes of interest, and their applicability is likely limited to usage cases where extremes of usage are not experienced.

3.2.3 Physical aging model-based derating

A physical aging model describes the fundamental degradation processes in a battery, providing a description of charge carrier transport as well as chemical and electrochemical reactions which can be used for derating[91]. Yin et al.[33] considered different limiting factors, such as surface ion concentrations, SOC, cut-off voltage, and side reaction rate to generate different charging protocols and implemented these charging methods in real time using a battery-in-the-loop (BIL) system. Experimental results demonstrated that the charging method limited by surface ion concentration and side reaction rate showed the best performance, with charging time reduced by more than 40% while maintaining the aging speed compared to the charging method recommended by the manufacturer. The physical model-based derating approach allows the direct control of the internal states, however, parameterization of key model variables remains challenging.

3.2.4 Machine learning aging model-based derating

With the emergence of artificial intelligence techniques, ML methods are becoming increasingly popular in the battery field[1,8], with notable efforts applying ML towards learning battery aging behaviour and extending its lifetime. Aitio et al.[92] used probabilistic ML techniques to learn internal resistance as a function of current, temperature, SOC, and time, towards calibrating SOH, achieving accurate end-of-life prediction using the field data. Bibinsha et al.[34] presented a ML model which can reproduce battery capacity loss and from this proposed a SOC-based derating method, with a simulated lifetime extension of 2.03%.

3.3 Comparison of static derating methods

Table 4 highlights the advantages and disadvantages of heuristic and model-based derating methods. Heuristic approaches are simple to formulate based on experimental results but may not be optimised due to limited testing. With the aging model, a more optimal derating method can be developed, but a significant number of aging tests are needed for model parameterization, and internal states/parameters of batteries are not easy to calibrate.

Table 4 Advantages and disadvantages of static derating methods, as well as potential applications.

Derating method	Advantages	Disadvantages	Potential applications
Temperature SOC Voltage Resistance	• Simple to develop	• Might not understand the aging comprehensively • Might not result in optimal solution	• Cases where only limited aging data or prior aging tests/knowledge is available
Other characteristic	• Simple to develop if the state can be monitored	• Can be challenging to obtain the state, such as the anode potential	• Cases where only the state, such as the anode potential is available
Hybrid metric	• Simple to develop if several characteristic metrics are monitored	• Might lead to the over-derating	• Cases where battery aging under several characteristic conditions is clear
Performance model	• Easy to develop	• The aging behaviour is uncertain	• Cases where only battery aging is reflected in the performance
Empirical aging model	• Possible to achieve a more optimal solution	• Extensive aging tests needed to parameterize the model	• Applications where lots of aging and parameterisation is available
Physical aging model	• Can estimate internal states • Possible to achieve a more optimal solution	• Aging tests needed to parameterize the model • Internal states/parameters are not easy to validate	• Applications where few aging, parameterisation and performance data is available
ML aging model	• Possible to achieve a more optimal solution	• Extensive aging tests needed to train the model	• Applications where lots of aging and parameterisation data is available

We quantify the lifetime extension and derating factor of the experimentally validated static derating methods using Eqs (1)-(4), as illustrated in Table 5. When the derating factor is less than one, the derating methods extend battery lifetime by a maximum of ~400% and a minimum of ~41%. Three SOC-based derating cases are quantified, in order to highlight that lifetime extension under the same derating factor can vary for different batteries and/or aging conditions. When the derating factor is higher than 1, which indicates fast charging, the lifetime in some cases is kept almost the same. This is mostly attributed to the Li plating prevention current being higher than the suggested current from the manufacturer. One promising derating approach presented by Spingler et al.[28] illustrates an increase in both battery lifetime and performance, likely because the Li-plating onset limit allows a larger charging current compared with the traditional method.

Table 5 Quantitative comparison of static derating methods in terms of lifetime extension and derating factor. Only the experimental results are presented and analysed.

Derating methods	Lifetime extension (%)	Derating factor (δ)	Explanation	References
SOC	286.2[a]	0.6 (20-80% SOC)	NMC/Gr battery; 0.5C cycling at 25 °C	Preger et al.[58]
	400.7[a]	0.2 (40-60% SOC)		
	83.4[b]	0.6 (20-80% SOC)	LFP/Gr battery; 1C cycling at 25 °C	Jiang et al.[56]
Voltage	41.1[b]	0.917 (4.1V CV charging)	LCO/Gr battery; 1C cycling at 25 °C	Gao et al.[23]
Resistance	44.0[b]	0.891 (Resistance based charging)	NCA/Gr battery; 1/2 C discharge at 25 °C	Sebastian et al.[26]
Other characteristic	19.3[b]	1.120 (Li plating prevention-based multi-stage CC charging)	NMC/Gr battery; 1 C discharge at 25 °C; Compared with 1C CCCV charging	Spingler et al.[28]
Hybrid metric	~0[b]	2.130	NMC811/Gr battery; 25 °C multi-stage CC charging with the anode potential and temperature limits	Liu et al.[29]
Physical aging model	~0[b]	1.78	NMC/Gr battery; 25 °C multi-stage CC charging; Compared with 1C CCCV charging	Yin et al.[33]

[a]Calculated with Eq.(3); [b]Calculated with Eq.(4).

4 Dynamic derating

Dynamic derating approaches are ones that change their derating parameters with battery aging, as illustrated in Fig. 5. Capacity loss[93,94], and resistance increase[95,96] are two common metrics to indicate battery health and they are thus used to regulate the current/voltage. Other health indicators, such as Li plating, which is the most prominent aging mechanism that leads to fast degradation of batteries[43,97,98]. Here, defining the Li plating prevention boundary is used to modulate the current/voltage. However, the reality is that Li plating is also influenced by other degradation modes[7,99], and thus models which capture the behavior of several aging effects are needed to develop an effective derating method. Here, more than eight dynamic derating methods are summarized and compared with quantitatively assessed of the lifetime extension and performance.

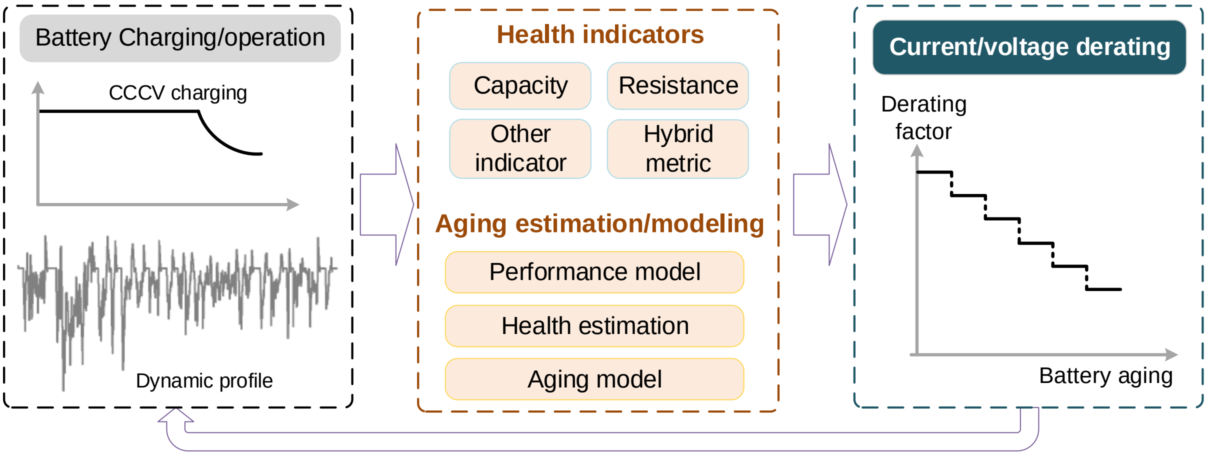


Fig. 5. Flowchart of dynamic derating methods

4.1 Heuristic methods

4.1.1 Capacity loss-based derating

The capacity loss-based derating method refers to approaches which regulates the current (voltage/power) with capacity loss (Eq. (5)). Epding et al.[35] used a three-electrode cell to determine the appropriate charging current for developing a fast-charging protocol without significant aging, and proposed a dynamic derating approach that reduces the charging current with the capacity loss. Keil et al.[36] explored derating with different constants of proportionality relative to the capacity loss (κ, Eq. (6)) and showed that derating with an adaptation factor of 4 ($\kappa = 4$) is needed to avoid non-linear degradation. An adaptation factor of >>1 is required, likely because the initial charging current (1C, the maximum permission charging current) is much high for their investigated battery. Koleti et al.[37] formulated a CC-CV-CC charging method and modulated the CV voltage with capacity loss, which extended battery lifetime by 75% compared with the traditional method. Sieg et al.[38] used a three-electrode cell to determine the charging current and presented a CC-CV$_{neg}$-CV (V$_{neg}$= negative electrode voltage) fast charging method, with the charging current decreasing with capacity loss (Eq. (5)). Compared with the traditional charging method, the presented fast charging approach fails to extend battery lifetime, which may be attributed to the unsuitable derating strategy.

$$I_{k+1} = I_{initial} \cdot \left(1 - Q_{\mathrm{loss},k}\right) \tag{5}$$

$$I_{k+1} = I_{initial} \cdot \left(1 - \kappa \cdot Q_{\mathrm{loss},k}\right) \tag{6}$$

In Eq. (5) and Eq. (6), I_{k+1}, $I_{initial}$, $Q_{\mathrm{loss},k}$, and κ, represent the applied current (or voltage) at the next time step, the initial current (or voltage), the current capacity loss, and the adaptation factor, respectively.

4.1.2 Resistance change-based derating

The resistance change-based derating method is one that regulates the current (voltage/power) with battery resistance change, as shown in Eq. (7), which approximately holds the polarization voltage constant[34]. Sieg et al.[38] calculated the 10s resistance as a cell degraded, and utilised it to modulate the charging current (Eq. (7)). Koleti et al.[39] showed that the resistance would decrease once Li plating occurred due to the higher activity of lithium vs Gr, and developed the resistance change-based derating method. Using online and offline resistance measurement methods, the derating method extended battery lifetime by 75% and 250%, respectively. The offline method is more effective as it can accurately estimate the onset point of Li plating due to the many available data for deep analysis.

$$I_{k+1} = I_{initial} \cdot \frac{R_0}{R_k} \tag{7}$$

For Eq. (7), R_k, and R_0 represent the current and initial resistance of batteries, respectively.

4.1.3 Other health indicator-based derating

Other health indicator-based derating methods refer to approaches that modulate the current (voltage/power) as a function of other aging indicators, such as Li plating signals. Koleti et al.[33]

used the voltage relaxation profile and the dV/dQ approach to detect Li plating and changed the CV hold voltage, which extended battery lifetime by 45% compared with the traditional method. Later, Koleti et al.[37] presented a resistance change-based Li plating detection method, and used it to regulate the charging current, with battery lifetime extended by more than 75%. For battery charging, the Li plating prevention-based derating approach can be considered the most useful method to extend battery lifetime if the Li plating can be detected. In the real world, it is not easy to detect Li plating. For example, irreversible Li plating cannot be easily observed with the dV/dQ method[11,100,101] and battery resistance would be affected by other parameters, such as temperature[59,60,102]. Therefore, an effective Li plating detection method is critical for this derating approach.

4.1.4 Hybrid metric-based derating

The hybrid metric-based derating method refers to approaches where the current (voltage/power) decreases based on several health metrics, such as the minimum of derating factors calculated from the capacity loss and resistance change (Eq. (8)). Both the capacity and resistance are commonly considered key battery health indicators[63], and using these two is proposed to effectively prolong battery lifetime. Sieg et al.[38] considered both the capacity loss and the increase of the 10s resistance, and used their minimum to regulate the charging current (Eq. (8)). Initially, the capacity degraded and battery resistance slightly decreased, and the charging current was thus reduced with capacity loss (Supplementary Figure S2). After 600 cycles, the resistance increase was high and the charging current was regulated by the resistance increase. Despite fast charging with a charging time of less than 23 mins, this derating method extended battery lifetime by 24.1%, compared with a traditional charging method (~40min).

$$I_{k+1} = I_{initial} \cdot \min\left((1 - Q_{\mathrm{loss},k}), \frac{R_0}{R_k} \right) \tag{8}$$

4.2 Model-based derating

4.2.1 Performance model-based derating

The performance model-based derating method refers to one that updates the current (voltage/power) based on calculations of a performance model with re-parameterization using aging data. Guo et al.[40] formulated a lumped equivalent circuit model, with model parameters updated with battery aging, and employed it to calculate the charging current to track the so-called universal charging voltage. This method extended battery lifetime by 290% while keeping a short charging time compared with the traditional method.

4.2.2 Health estimation-based derating

The health estimation-based derating refers to approaches that accommodate the current (voltage/power) with the estimated/diagnosed battery health. As it is challenging to measure battery health indicators, such as the available capacity, in the real world due to a lack of full charging/discharging cycles, battery health estimation/diagnostic methods are particularly important when implementing aging adaptive derating[103]. Lee et al.[41] measured the voltage change (ΔV) at SOCs of less than 80% to estimate the capacity degradation based on their fitting equation, and then modulated the charging current with Eq.(5). Compared with the standard CC charging, the dynamic derating-based charging method extended battery lifetime by 47%.

4.2.3 Physical aging model-based derating

Physical aging model-based derating refers to approaches that update the current (voltage/power) with the internal aging variables. For example, Mandli et al.[42] presented an aging model that mainly considered the SEI growth and used a genetic algorithm to balance charging time and battery life to determine the charging current. This derating method extended battery lifetime by 2% and this low extension may be attributed to the fact that other aging mechanisms dominate the battery degradation. The physical model-based derating approach features the direct control of the internal states/parameters, however as the battery ages, the tracking and re-parameterization of key model variables remains a key uncertainty.

4.2.4 Hybrid model-based derating

Hybrid model-based derating refers to approaches that modulate the current (voltage/power) with the calculations of several models. Jin et al.[104] used an integrated electro-thermal-aging model to formulate an aging-aware optimal charging strategy considering the aging status and performance dynamics. Su et al.[43] developed an approach which incorporated a performance model, physical aging model and ML model, and used an optimization method to adaptively adjust the charging current for achieving a balance between the charging time and capacity degradation under different aging states. Here, the charging current decreased from 4C to 3C over 3000 cycles and the charging simulation indicated that the average charging time decreased by 24.2% and the capacity loss was almost identical, compared with 1C CCCV standard charging. No lifetime extension is likely attributed to the high initially charging current used, and therefore, determining an appropriate charging (discharging) current for the fresh cell is critical to achieve an effective dynamic derating.

4.3 Comparison of dynamic derating methods

Table 6 compares the advantages and disadvantages of dynamic derating methods. As the capacity loss and/or resistance increase is often obtained, the capacity loss-, resistance change- and hybrid metric-based derating approaches are simple and easy to implement. The drawbacks, however, are that these SOH indicators do not necessarily reflect the dominant aging factor[9,105], with this leading to over or under derating. For battery charging, the Li plating prevention-based derating method is driven by the Li deposition behaviour[11,106] making the approach more physically driven and likely to be optimal for charging. Heath estimation-based derating methods modulate the current/voltage from the perspective of real world applications. The aging model-based derating method considers many aging modes and is a promising method to extend battery lifetime. However, the challenge is whether all degradation mechanisms are captured and how key parameters for this are captured.

Table 6 Advantages and disadvantages of dynamic derating methods, as well as potential applications.

Derating method	Advantages	Disadvantages	Potential applications
Capacity loss	• Simple/easy to implement • Captures multiple coupled degradation modes	• Possible under-/over-derating • No specific physical meaning	Batteries with capacity easily identified and capacity loss mainly corresponding to the dominant aging mechanism
Resistance change	• Simplest/easiest to implement • Captures multiple coupled degradation modes	• Possible under-/over-derating • No specific physical meaning • Might be influenced by other parameters, such as temperature and SOC	Batteries where the prominent aging mechanisms highly depend on the resistance
Other health indicator, such as Li plating prevention	• Avoids Li plating • Significant physical meaning	• Challenges of detecting Li plating over the lifetime for different battery chemistries • Online detection difficulty • Only considers charge behaviour	Batteries where Li plating is easy to detect and where fast charging is important
Hybrid metric	• Greatly extend battery lifetime • Captures multiple degradation modes	• Not easy to balance several parameters • Might over-derating • Challenges of obtaining aging dependent parameters	
Performance model	• Consider the electrical/thermal/mechanical/electrochemical limits/states	• Cannot provide the primary aging factors, and not directly control the internal aging variables	
Health estimation	• Consider the real world applications, estimate battery health states rather than measure them	• Challenge to know the degradation details	Batteries with an accurate health estimation
Aging model	• Considers the main degradation mechanisms • More degradation details are likely considered	• Need extensive aging tests • Some aging mechanisms are not easy to be captured by models • Degradation model may deviate from the real-world battery behaviours	Batteries with a large aging data sets

We quantify the lifetime extension and derating factor of the experimentally validated dynamic derating methods, as displayed in Table 7. As the derating factor changes with battery aging, the maximum and minimum values and the median/mean value of derating factors are presented to show the decreasing current/voltage. When the derating factor is less than one, the derating methods extend battery lifetime by a maximum of 290.7% and a minimum of 45.4%. For the capacity loss-based derating methods demonstrated by Sieg et al.[38], the average derating factor is 1.714 and the lifetime is decreased by 36.1%. However, with the hybrid metric-based method, despite the high derating factor of 1.409, the lifetime is prolonged by 24.1%, indicating the significant advantage of this method. This was achieved by the high reduction of charging current after ~600 cycles using the derating factor from the metric associated with resistance increase (Supplementary Fig. S4), and thus no extensive Li plating.

We observe that some of the derating factors are near or above 1, which is attributed to varying baselines between the derating and the regular method (reference). For example, the derating method from Epding et al.[35] is compared with charging at 2C, while the fast charging method from Sieg et al.[38] (<23 min) is assessed with slow charging (~40 min). This indicates an unfair comparison, and leads to the challenge to evaluate the derating methods. Thus, more comparative presentation of testing results is needed moving forward.

Table 7 Quantitative comparison of dynamic derating methods in terms of lifetime extension and derating factor. Only the experimental results are presented and analysed.

Derating methods	Lifetime extension (%)	Derating factor (δ)		Explanation	References
		Median/mean	Min.-Max.		
Capacity loss	85.6[b]	~1[c]		NMC622/Gr battery; 23 °C multi-stage CC charging;	Epding et al.[35]
	79.9[b]	0.693	0.52-1.0		Keil et al.[36]
	71.2[b]	0.958	0.929-0.958		Koleti et al.[37]
	-36.1[a]	1.714	1.501-1.927	25.5 °C; Charging current shown in Fig. S3	Sieg et al.[38]
Resistance change	Online: 75[a]; Offline: 250[a]	Online: 0.962; Offline: 0.883			Koleti et al.[9]
Other aging indicator	45.4[b]	0.988	0.952-1.0		Koleti et al.[37]
Hybrid metric	24.1[a]	1.409	1.099-1.719	25.5 °C; Charging current shown in Fig. S3	Sieg et al.[38]
Performance model	290.7[a]	~1[c]		LCO-NMC/Gr battery; Varying charging current profile shown in Fig. S4;	Guo et al.[40]
Health estimation	47.0[b]	0.908	0.816-1.0		Lee et al.[41]

[a]Calculated with Eq.(3); [b]Calculated with Eq.(4); [c]Compared with 2C charging

5. Industry considerations for derating methods

Within industrial applications, many electric vehicle manufacturers offer guidance to make the battery last longer based mostly around user behaviours (Fig. 6, Table 8). For instance, MG Motor published a guide to electric car battery life and suggested reducing the exposure to extreme temperatures[107]. Qualitatively, they suggest, when parking in hot weather, to find a spot in the shade to keep the battery cooler. During the winter, they recommend parking in a garage, rather than on the street.

BYD experts highlighted that it is not advisable to leave the battery at 100% SOC for more than 8 hours[108], and recommended that full charging should be avoided if possible. This is likely to minimise the electrolyte decomposition and SEI layer growth effects noted earlier but one additional benefit of not fully charging is that it leaves capacity to store energy from regenerative braking. Furthermore, MG Motor stated that keeping the battery at a level of between 20 and 80% SOC is ideal for everyday usage[107].

Chargemap suggested minimizing the frequency of fast charging[109], especially when the battery is already heated up, which likely leads to a highly elevated temperature. After the battery ages, fast charging likely drives the anode potential further negative, especially with a high anode degradation, which more readily triggers Li plating. Thus, BOSCH presented a health charging mode[110] that can quickly charge the battery without compromising battery lifetime. One of the promising avenues to achieve this method is to develop a cloud-based battery management system (BMS)[111,112]; for instance, use battery data from the connected vehicle in combination with electrochemical models in the cloud to identify battery stress factors and actively helps to reduce them.

Some proprietary technologies have explored derating methods to potentially prolong battery lifetime (Fig. 6, Table 8), though most of them have yet to be put into real-world application. Tesla filed a 2015 patent describing a distinct and comprehensive 'battery life mode', which calibrates BMS parameters to favour battery lifetime over vehicle range and performance[113].

Strategies adopted include narrowing the SOC range, narrowing cut-off voltages and limiting charging/discharging currents. Panasonic described a lifetime estimation approach and then presented a deterioration suppressing method, by decreasing the charge cut-off voltage and increasing the discharge cut-off voltage[114]. Hyundai reduced the output current and narrowed the operation voltages if the load is higher than the set point[115].

Murata patented a hybrid metric-based static derating method that decreases the charge/discharge current at low temperatures while narrowing cut-off voltages[116]. For example, at -10°C, the charging current is reduced to 0.1C and the cut-off voltage is set as 3.5V for their LFP battery. Ford illustrated a lifetime extension method, which adjusts the SOC operation window over a predefined time[117]. However, how to determine the SOC limits remains uncertain.

Toyota patented an approach to suppress the occurrence of side reactions by controlling the output current/power to change the positive and negative electrode (PE, NE) potential within a range between upper and lower limit values respectively[118]. The electrode potential can be detected by placing a reference electrode or can be estimated by comparing the OCV of the full cell (FC) and the PE and NE potentials. This method seems promising, however, it is challenging to obtain the electrode potentials and determine the upper/lower limits.

Traditional automotive original equipment manufacturers (OEMs) have shown reluctance to introduce life-adaptive performance derating, even if it extends life, due to risks of negative customer perception. This reluctance extends to recommending battery-preserving behaviors, such as reducing charge SOC limits or limiting rapid charge frequency, due to concern over exacerbating customer anxiety. Conversely, the new generation of EV manufacturers opt for a more transparent approach. This is seen in Tesla’s ‘standard trip’ mode, which decreases the charge limit to 90% SOC from 100% in ‘trip’ mode[119], and Polestar recommending a 90% SOC daily limit in the user interface[120].

In order to build consumer confidence for EVs, breakthroughs in the mainstream societal anxieties around battery lifetime and range must be addressed. Dynamic derating strategies must be carefully designed to maintain customer experience as much as possible, which means opting for derating strategies that pose less perceptible impacts on the customer. Battery health monitoring is imperative for dynamic derating, and opportunities exist in estimating/diagnosing the health of batteries from charging as this is the most controllable period within the usage pattern. Doing so safely, and with appropriate derating to avoid positive degradation feedback loops, will become increasingly important moving forwards.

Battery degradation modelling and diagnostics are further complicated in the real-world due to a tendency towards large parallel groups of cells, monitored by a single set of sensors (i.e. current, voltage, temperature), which limits the applications of derating strategies. These cells may be subjected to unequal thermal conditions and current densities, and can therefore undergo heterogeneous degradation, limiting the accuracy of degradation diagnostics and influencing the resultant formulation of derating control.

While typical automotive OEM BMS hardware is usually not suitable for large batch processing diagnostics, the maturation of connected vehicle telematics and cloud-hosted data is unlocking new opportunities for advanced diagnostics. This is promising in enabling data-informed modeling and effective derating methods using field data.

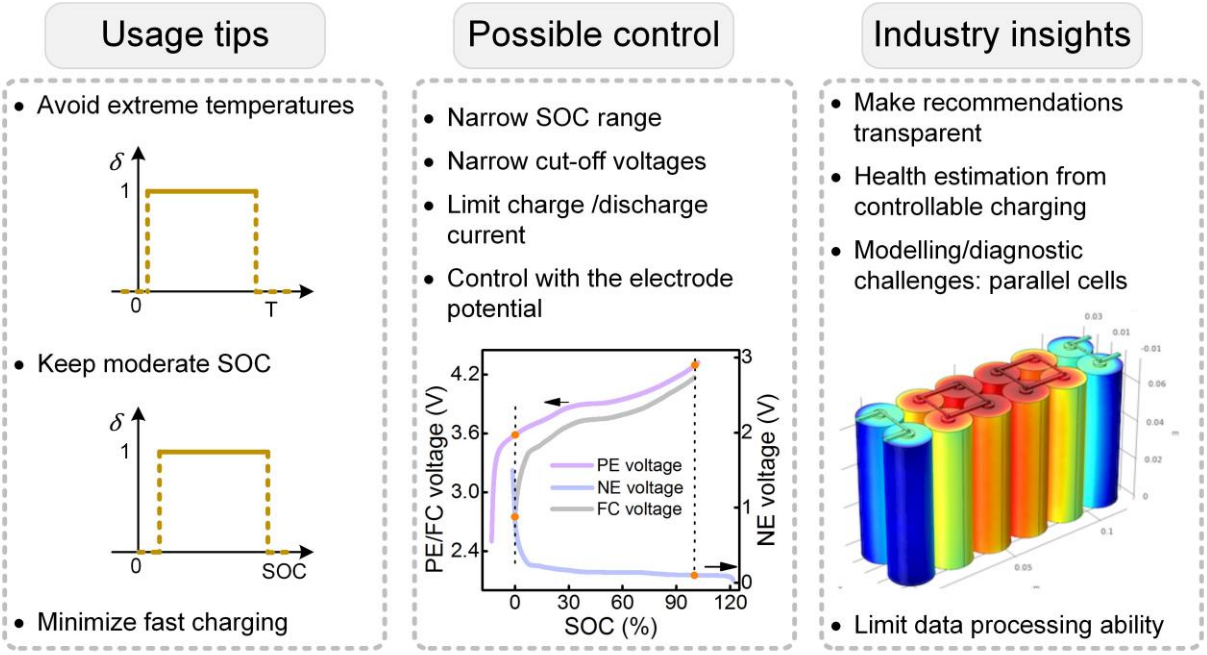


Fig. 6. Industry considerations for derating methods

Table 8 Summary of derating guidance/control in industry.

Derating guide/control	Derating categorisation	Example industry application
Reduce exposure to extreme temperatures	Temperature-based static derating	MG Motor[107]
Reduce time at 100% SOC; Avoid fully charging	SOC-based static derating	BYD[108]
Keep the battery between 20-80% SOC	SOC-based static derating	MG Motor[107]
Minimize fast charging at high temperatures	Temperature-based static derating	Chargemap[109]
Narrow the SOC range	SOC-based static derating	Tesla[113]
Narrow cut-off voltages	Voltage-based static derating	Tesla[113]
Decrease the charge cut-off voltage & increase the discharge cut-off voltage	Voltage-based static derating	Panasonic[114]
Narrow the operating voltages if the load is high	Voltage-based static derating	Hyundai[115]
Reduce the current at low temperatures & narrow extreme cut-off voltages	Hybrid metric-based static derating	Murata[116]
Adjust the SOC operation window	SOC-based static derating	Ford[117]
Manage PE and NE potential	Other characteristic-based derating	Toyota[118]
Recommend a 90% SOC daily limit	SOC-based static derating	Polestar[120]

In summary, the process of designing any BMS control strategy for an electrified product, requires a balance between ‘hard’ derate limits that maximize headline performance within safety constraints, and ‘soft’ limits that promote enhanced lifetime. Improved modelling and control of battery degradation, enabled by improved sensors, processors, and telematics, are crucial to rightsizing battery packs in their design, and enabling the maximum economic benefit over their lifetime. The degree of freedom that derating strategies can be afforded is highly dependent on the sector and customer expectations; for consumer applications, the need to manage and prioritize customer perception cannot be overstated.

6. Perspectives and future directions for derating methods

6.1 Considerations in choice of derating strategies

Battery degradation is complicated and affected by chemistry, operating conditions and design. This leads to the challenge of selecting the most appropriate derating technique. For fresh cells, one should consider static derating with several thresholds (Fig. 7a). In general, the temperature, SOC and voltage should be measured and updated during operation. Thus, basic static derating methods, i.e. temperature-based, SOC-based and voltage-based derating approaches, can be adopted, to extend battery lifetime[3,4,121]. However, questions remain about how to determine the appropriate boundaries of temperature, SOC, and voltage with as few experiments as possible.

If the energy efficiency is the key consideration, resistance-based derating approach are preferred. The resistance adaptive current results in low energy waste and a roughly constant polarization voltage. Anode potential-based static derating is promising in developing battery fast charging, which prevents Li plating and the resulting accelerated degradation, however, estimating anode potential is challenging in the real world. If an aging model is developed, model-based static methods provide further options for derating, and it is possible to formulate an optimal derating method by balancing several control objectives.

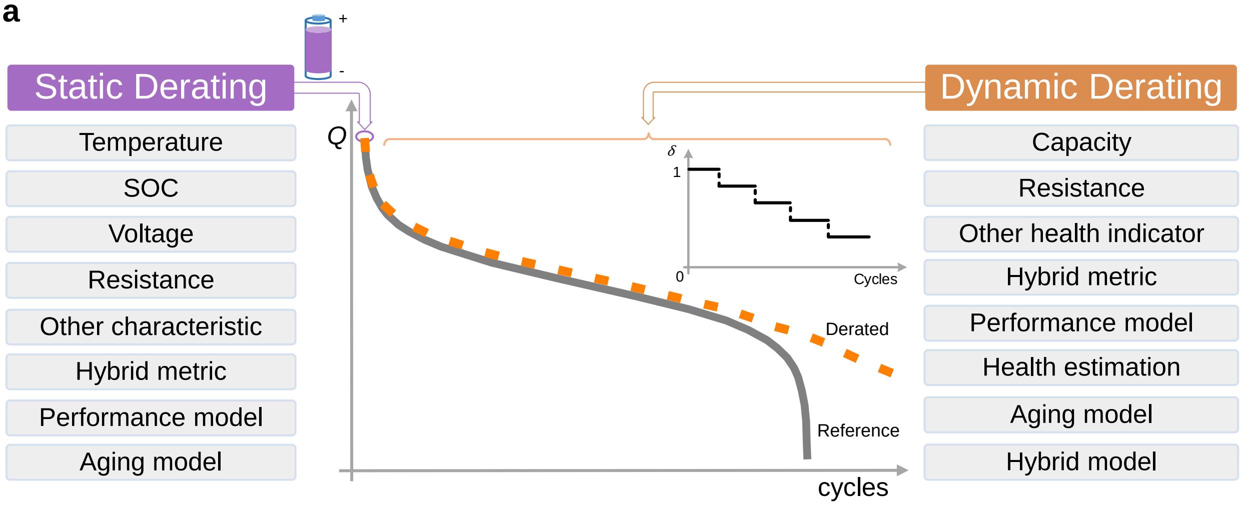
With the operating current/voltage restricted by static battery states, we should consider aging adaptive derating (Fig. 7a). SOH-based dynamic derating methods, i.e. capacity and/or resistance change-based approaches, are simple to implement as battery SOH is generally monitored. But it remains uncertain which SOH-based derating method is better.

If Li plating can be effectively detected, the Li plating prevention-based derating method is a superior approach for battery charging. However, this only considers Li plating as a degradation mode. Therefore, combining an effective Li plating detection method and an aging model is strongly desired.

When multiple static limits, such as temperature, SOC, and voltage limits, are applied in derating control, a further limit should be considered due to the influence of the operation conditions, with an example shown in Fig. 7b. The exploration of determining further limits in future studies is thus significant.

The derating control highly depends on the applied current (Fig. 7c), with a high current generally accompanied by a narrowed SOC range or low charging cut-off voltage[122,123]. Furthermore, the current waveform influences the derating control: the preferred dynamic derating approach would vary with different charging profiles[124]. The determination of an appropriate derating approach that adapts to applied current profiles remains uncertain.

a



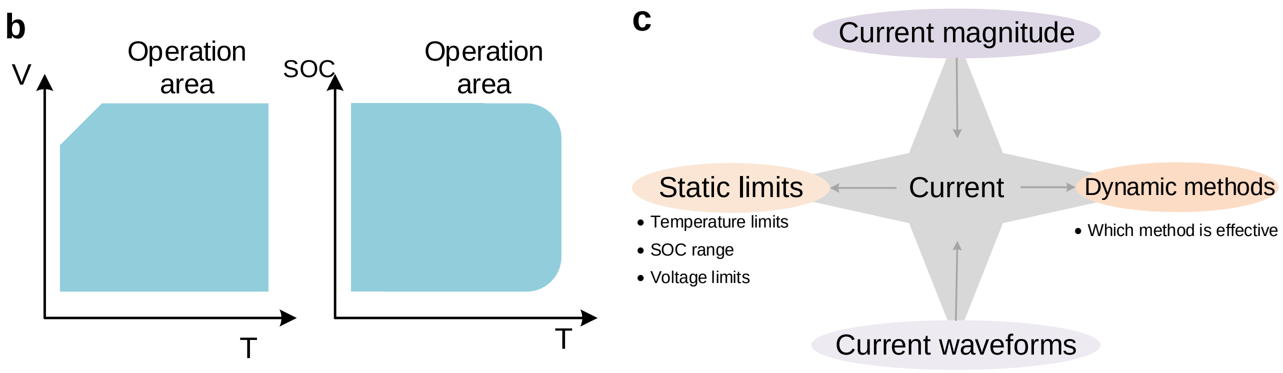


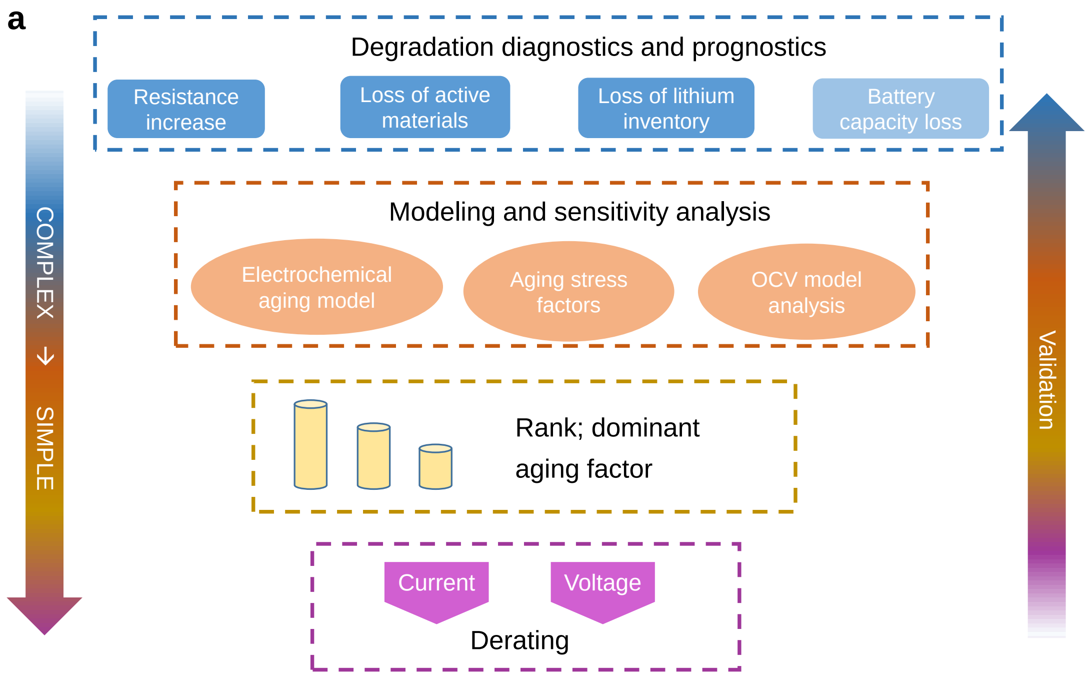
Fig. 7. Considerations in choice of derating methods. a. Effective derating of batteries based on both the static limits and aging states; b. An example of a further limit consideration when multiple static limits are used; c. The potential influence of the current magnitude and current waveforms on the static limits and dynamic methods.

6.2 Advanced dynamic derating

With emerging techniques, such as machine learning-based diagnostic and prognostic methods[8,125,126,127], we propose an advanced dynamic derating framework, as illustrated in Fig. 8a. This framework explores the interplay between coupled degradation mechanisms, establishes an aging model, searches for the dominant aging stress factor and determines a suitable derating approach. Battery degradation states, such as the anode and cathode material loss and resistance increase, would be identified first to understand the root aging mechanisms. Then, a physics-based aging model can be developed to capture battery degradation behaviour, with the diagnosed states being used to update the aging model. Using sensitivity analysis, aging stress factors can be ranked to determine the dominant stress factor. This would guide users on how/when to derate the current/voltage. Derating tests can be used to validate the diagnostic, modeling and analysis procedures, enabling a close loop advanced derating method, which forms a 'digital twin' of a real battery[111], aiming at both excellent performance and lifetime extension.

6.3 Hybrid derating

We often determine the temperature/SOC/voltage limits using the degradation data, such as capacity degradation[19-22,44-55], but the degradation profile is generally an average result when the battery reaches end-of-life. In different aging states, different static limits have varied influence on battery degradation. We thus propose the use of hybrid derating approaches, where the static limits are changed with battery aging, with an example shown in Fig. 8b. For a fresh cell, the temperature/SOC limits can be wide to enhance battery performance, and with battery aging, these limits should be gradually narrowed to circumvent fast degradation. This fused derating approach, incorporating the static and dynamic derating concepts, is expected to extend battery operation range and promote battery performance while limiting battery degradation. It remains an open question how to determine the operating limits in each aging stage.



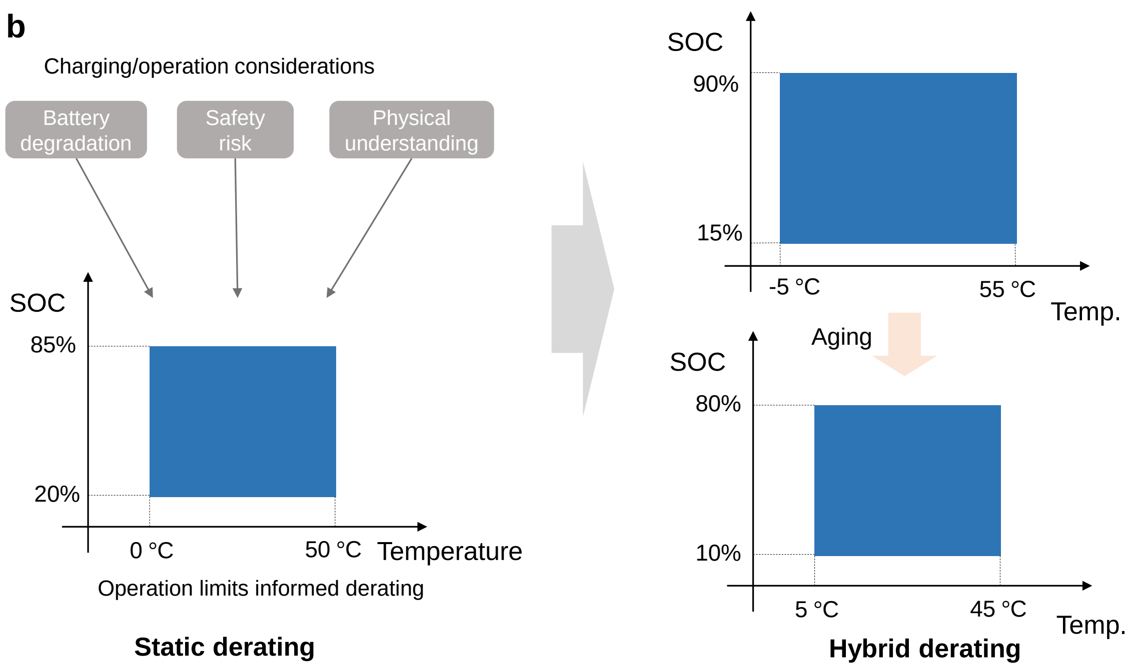


Fig. 8. Next-generation derating methods. a. Advanced dynamic derating methods; b. Hybrid derating methods.

7. Conclusions

We present a critical review of derating methods to promote this powerful but underestimated battery lifetime extension strategy. We first categorize derating methods as the dynamic and static approaches, based on whether the derated parameters changed with battery age or not, with further classification as heuristic or model-based techniques. The details, advantages, and limitations of these approaches are presented, evaluated and discussed, towards providing the underpinning insights.

When quantifying the performance implications of static and dynamic derating techniques, we find that derating factors less than 1 result in battery lifetime extension between 41%-400% for the experimentally validated derating methods considered. Even if the derating factor is higher than 1 (indicating fast charging), an appropriate derating approach, i.e. the hybrid dynamic approach, has been shown to prolong battery lifetime by 24%, which may be explained by no extensive Li plating due to the reduction of charging current after ~600 cycles using metrics associated with resistance increase. This benefit, achieving not only fast charging but also a long lifetime, highlights the significant advantages of derating methods.

The complicated battery degradation pathways involved poses a challenge in selecting an appropriate derating approach. In static derating, determining the temperature, SOC or voltage limits, remains challenging, as improper parameters may not prolong battery lifetime. The SOH-based method can be considered as the basic dynamic derating approach as the SOH is often monitored but the challenge lies which derating method (capacity loss, resistance increase and hybrid metric) is optimal.

Developing a deep understanding of the degradation modes is the key for an optimsed dynamic derating approach. Thus, we propose a derating framework based on digital twins, which includes diagnostics, prognostics, aging modelling, and sensitivity analysis to find the dominant aging stress factor, towards developing effective dynamic derating. Battery operation limits, such as the temperature, SOC, and voltage limits, should be regulated with aging and thus a hybrid derating approach, incorporating the static and dynamic derating concepts, is a future research direction, to maximize both performance and lifetime. However, it remains uncertain how to determine the operation limits, especially with battery degradation.

Acknowledgements

This work was kindly supported by the Faraday Institution's Industrial Fellowship (FIIF-013), the EPSRC Impact Acceleration Award (EP/X52556X/1), the EPSRC Faraday Institution's Multi-Scale Modelling Project (EP/S003053/1, grant number FIRG003), the EPSRC Joint UK-India Clean Energy centre (JUICE) (EP/P003605/1) and the EPSRC Integrated Development of Low-Carbon Energy Systems (IDLES) project (EP/R045518/1).

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