

Whitepaper

BREATHE

MODEL DISTILLATION FOR BATTERIES

Deriving Equivalent Circuit Models
from Physics-Based Models

Why battery models matter in design and control

Designing and controlling batteries is an exercise in uncertainty. Cells behave differently across chemistries, conditions, and ages, and it is rarely practical to measure everything in the lab. This creates a gap in our understanding of their behaviour in all use cases, one that we as an industry have historically tried to fill with costly, long, and resource intensive empirical testing.

Battery models address this gap differently. By using the empirical lab resources to generate battery models instead of raw test data, the leverage of lab resources to reveal understanding of battery behaviour takes a step change in depth of understanding, by providing access to internal states during virtual experiments, breadth by offering incredible gains on time to result, and cost reduction by shifting the burden of data generation to the virtual space.

Some areas where battery models can close the loop between understanding behaviour and design are in the design of charging strategies, evaluating safety margins, and managing performance at both cell and system level. For OEMs, models are critical to accelerating development while reducing cost and risk.

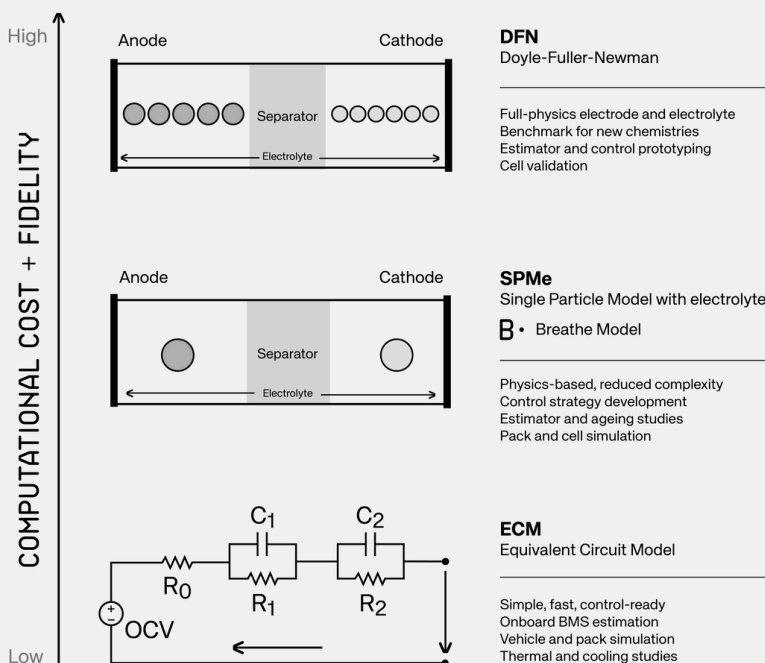
Different types of models exist for different purposes. For design, a model should relate the material and cell design choices to the measurable signals, while for control a model should simulate a measurable signal through which a control action can then be taken.

Equivalent Circuit Models (ECMs) are widely used because they are simple to compute and integrate easily into battery management systems. Physics-based models such as the Single Particle Model with electrolyte (SPMe) capture the underlying electrochemistry and can emulate cell internal states, while allowing for material design choices to be accounted for. However, their computational cost makes them less suitable for onboard control or large-scale pack simulations.

The opportunity lies in applying a concept familiar in machine learning: distillation. Just as large, complex models can be distilled into smaller, faster ones that retain their usefulness in deployment, an SPM can be distilled into ECMs. This enables control-ready models to be generated through simulation rather than exhaustive lab testing, reducing dependence on critical cyclers, costly experiments, and scarce specialist headcount. The result is a faster, more efficient pathway to the models that OEMs need for design and control.

The landscape of battery models: the right tool for the job

Battery models sit on a spectrum. At one end are full electrochemical descriptions, at the other are simplified circuits, and in the middle sit reduced-order physics models. Each has strengths and trade-offs, and the right choice depends on the job to be done.



The **Single Particle Model with electrolyte (SPMe)** makes deliberate approximations. Each electrode is represented by a single “average” particle, while electrolyte transport is described with a reduced form. This “macro-micro” simplification preserves access to the same internal states as DFN — solid-phase lithium concentration, electrolyte dynamics, electrode potentials — but with far lower computational demand. The result is a model that runs quickly enough for pack-level simulation and control development while still being grounded in electrochemistry. SPM can also be used to generate ECMs, offering a versatile “two for the price of one” workflow: physics-based simulation and control-ready models from the same foundation.

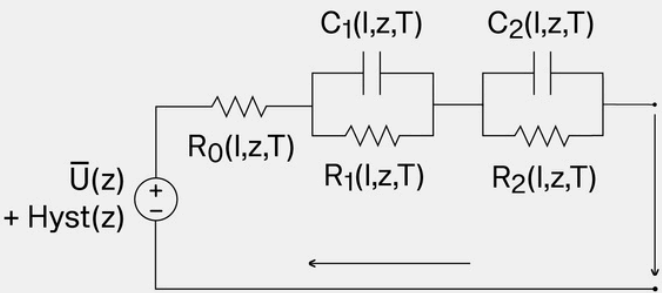
Equivalent Circuit Models (ECMs), by contrast, abstract batteries into resistance–capacitance networks fitted to experimental data. They are the simplest and fastest to run, making them ideal for real-time BMS control, vehicle-level simulation, and thermal studies. The trade-off is that they are empirical: they lack the explanatory power of physics-based models and require extensive lab testing for each new condition or aged state.

Equivalent circuit models: simple, practical, control-ready

Equivalent Circuit Models (ECMs) are the most widely used battery models in control and system simulations. They reduce a cell to a voltage source combined with a set of resistors and capacitors that reproduce the terminal voltage response to applied current. By abstracting away detailed electrochemistry, ECMs run quickly, scale easily to large packs, and are simple enough to embed in a Battery Management System (BMS).

The most common variant in industry is the 2-RC model, shown in the diagram. At its core is the open-circuit voltage source $\bar{U}(z)$, which depends on the cell's state of charge: z . A hysteresis term $\text{Hyst}(z)$ accounts for the offset between charge and discharge open circuit voltage. The series resistance $R_0(l,z,T)$ models the instantaneous voltage drop when current flows, where l is applied current (positive for discharge) and T is temperature. The two parallel resistor–capacitor branches (R_1, C_1) and (R_2, C_2) represent dynamic processes with different time constants, capturing both fast surface effects and slower diffusion relaxations. Their values also depend on l , z , and T , ensuring the ECM adapts to different operating conditions such as high C-rates, deep cycling, or low-temperature operation.

ECM
Equivalent Circuit Model



This compact structure is sufficient to replicate the behaviours that matter most for applications: the nonlinear relationship between state of charge and voltage, the immediate ohmic drop under load, and both fast and slow transient responses. Despite its simplicity, the 2-RC ECM delivers enough fidelity to support critical functions:

State estimation with Kalman filters

Accurate SoC and SoE tracking under dynamic drive cycles.

Thermal control integration

Electrical losses in R_0, R_1, R_2 can be mapped into heat generation for electro-thermal control.

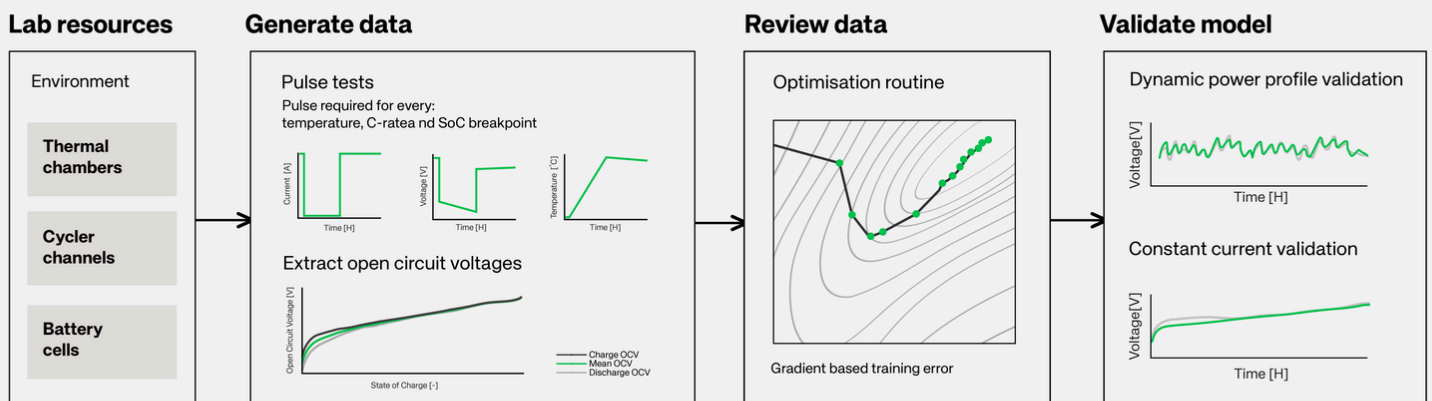
Pack and system simulations

Lightweight enough to scale to thousands of cells while still reproducing realistic transients.

SoH tracking and ageing indicators:

Changes in resistance and capacitance values provide simple degradation signals.

Traditional ECM methods: curve fitting and empirical limits



Building an Equivalent Circuit Model (ECM) through traditional methods is a resource-intensive exercise. Cells, battery cyclers, and thermal chambers are the essential inputs, and from there, a set of structured tests must be carried out. The goal is to generate resistance-capacitance parameters that reproduce the cell's dynamic voltage response, but every parameter comes at the cost of experimental time, specialist oversight, and equipment utilisation.

Pulse tests

Pulse testing is the cornerstone of empirical ECM parameterisation. Each pulse test is used to extract values for the instantaneous resistance (R_0), dynamic resistances (R_1 , R_2), and associated capacitance (C_1 , C_2).

To achieve usable accuracy, these tests must be repeated across a grid of operating conditions: every temperature of interest, every State of Charge (SoC) breakpoint, and every C-rate level at which the model should remain valid. Each new breakpoint adds another set of tests, introducing a direct trade-off between accuracy and cost.

A typical starting point for empirical ECMs contains 800 unique combinations:

- 8 C-rate breakpoints (4 charge, 4 discharge)
- 10 temperature breakpoints
- 10 SoC breakpoints

Optimisation routines

The raw experimental data does not directly yield the final parameter set. Instead, optimisation routines are run to ensure that the chosen R-C values recreate the measured pulse responses with minimal error. This process is repeated for every breakpoint, producing parameter maps that define resistance and capacitance as explicit functions of SoC, temperature, and current.

Open circuit voltage

The Open Circuit Voltage (OCV) curve defines the link between SoC and voltage. In many chemistries, a single OCV curve is sufficient to achieve the required accuracy, with only modest sensitivity to temperature.

For chemistries with pronounced hysteresis, such as LFP cathodes or silicon composite anodes, separate charge and discharge OCV curves are needed. A practical compromise is to store the mean OCV alongside a hysteresis term $H(z)$, defined as a function of SoC. This captures the shift in thermodynamic equilibrium between charge and discharge.

At Breathe, OCV characterisation is typically performed using C/50 charge and discharge tests, ensuring quasi-equilibrium conditions.

Validation

Once parameterised, the ECM is compiled into lookup tables that span the intended operating window. Validation is then carried out against conditions not used in training, such as WLTP drive cycles, CCCV charging profiles, or user-defined power demands.

Model accuracy is evaluated by comparing simulated outputs to experimental measurements, with typical error metrics including: Root Mean Square Error (RMSE), Maximum Absolute Error (MAE) and mean error.

Typical performance

Only once the errors are within acceptable bounds can the ECM be considered fit for control use.

Here is the accuracy of an empirical ECM generated at Breathe’s laboratory using the Molicel P45B

Results generated from Constant Current (CC) tests with full Depth of Discharge (DoD) and Depth of Charge (DoC).

Positive C-rate indicates charging, negative C-rate indicates discharging.

Voltage accuracy (RMSE)

RMSE < 50 mV RMSE ≥ 50 mV

		C-rate							
		-5.0 C	-3.0 C	-1.0 C	-0.5 C	0.5 C	1.0 C	3.0 C	5.0 C
Temperature	0°C	65.9	45.7	33.3	53.0	39.3	76.7	59.8	52.1
	5°C	53.8	45.8	48.3	46.5	45.9	58.9	76.0	71.3
	10°C	49.1	43.3	53.9	46.1	45.0	53.8	73.4	72.3
	15°C	50.9	48.5	32.7	34.3	42.0	46.9	66.8	75.0
	20°C	39.2	39.5	36.1	38.8	37.4	43.5	60.5	72.6
	25°C	48.5	46.2	25.7	33.6	40.9	43.2	53.7	75.9
	30°C	68.2	48.9	21.0	15.1	44.6	43.8	55.6	82.5
	40°C	50.0	41.1	21.5	22.4	38.5	41.4	54.5	75.4
	50°C	53.9	47.4	16.2	21.5	45.5	46.8	50.8	74.6
	60°C	65.0	58.9	14.9	10.7	44.3	48.0	61.2	108.0

Temperature accuracy (RMSE)

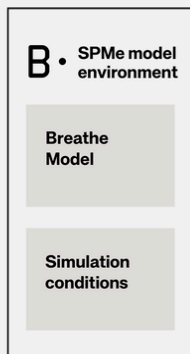
RMSE < 1.5°C RMSE ≥ 1.5°C

		C-rate							
		-5.0 C	-3.0 C	-1.0 C	-0.5 C	0.5 C	1.0 C	3.0 C	5.0 C
Temperature	0°C	2.5	2.0	0.9	1.3	1.3	0.8	0.7	0.5
	5°C	3.5	2.8	0.6	0.6	0.7	0.5	1.5	1.6
	10°C	5.1	3.9	1.4	0.9	0.7	1.0	2.3	2.7
	15°C	2.0	1.1	1.1	1.4	1.6	1.5	0.7	0.6
	20°C	3.3	2.4	0.8	0.5	0.7	0.5	0.9	1.5
	25°C	2.1	1.5	0.8	0.7	0.8	1.0	0.9	1.2
	30°C	1.6	1.3	0.7	0.6	0.6	0.8	1.1	0.8
	40°C	1.9	1.8	0.6	0.6	0.5	0.7	0.8	1.3
	50°C	1.6	1.3	0.8	0.8	0.8	1.1	1.6	1.2
	60°C	4.5	2.6	0.5	0.8	0.9	1.0	0.8	1.9

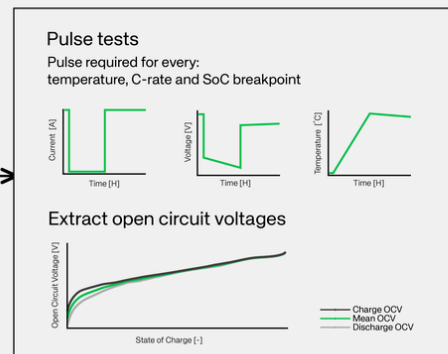
Distilling from physics: ECMs generated from SPM_e

Where traditional ECM parameterisation relies on lab-intensive pulse tests, an SPM_e offers a different route. By running virtual experiments inside a physics-based model, the same inputs can be generated synthetically, with far greater efficiency and control.

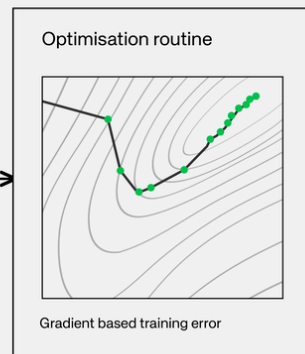
Simulation resources



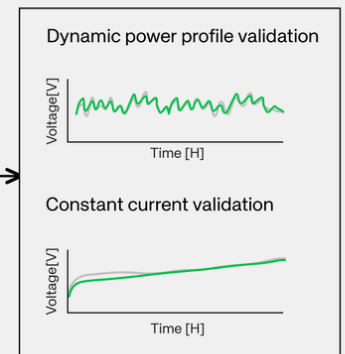
Generate data



Review data



Validate model



Virtual pulse tests

The SPM_e can be subjected to the same protocol as in the lab: pulses across temperature, C-rate, and SoC breakpoints. The difference is speed and scalability. Each breakpoint requires only two seconds of simulation time, meaning there is no practical penalty to increasing coverage. Instead of being forced to balance accuracy against resource consumption, engineers can parameterise ECMs across a dense grid of operating points.

Open circuit voltages

OCV curves can also be extracted directly from the SPMe, as they are part of its original construction, without incurring the time penalties of ultra-slow experimental tests by needing to regenerate this data empirically.

Charge, discharge, and mean OCVs can all be generated virtually, including hysteresis behaviour, ready for inclusion in the ECM formulation.

Fidelity carried through

The crucial insight is that when the original physics-based model contains sufficient fidelity, the distilled ECM retains enough accuracy and nuance for control applications.

At Breathe, we have consistently found that ECMs generated from Breathe Model preserve the essential behaviours of the cell across a wide operating window, while remaining light enough for real-time use or investigations at high system order (such as EV packs). This means engineers can achieve trusted control-ready models without the resource burden of exhaustive empirical testing.

Ready to run

Breathe's SPMe implementation, Breathe Model, comes with MATLAB scripts that encapsulate the full ECM generation workflow.

Breakpoints and parameterisation ranges are configured through a simple JSON file. Each pulse is simulated in seconds, with results automatically written to disk.

This makes integration straightforward: engineers can either continue with their own optimisation and validation routines or use the ones provided within Breathe Model.

Validating the distillation: physics-derived ECMs vs empirical ECMs

Results generated from Constant Current (CC) tests with full Depth of Discharge (DoD) and Depth of Charge (DoC).

Positive C-rate indicates charging, negative C-rate indicates discharging.

Breathe Model was parameterised with fewer breakpoints than the empirical ECM. Despite this reduced coverage, the ECM distilled from Breathe Model still achieved performance equivalent to the empirically generated ECM:

- Mean RMSE error:
- **Distilled ECM : 54.7 mV and 0.8°C**
 - **Empirical ECM : 49.2 m V and 0.9°C**

Voltage accuracy (RMSE)

RMSE < 50 mV RMSE ≥ 50 mV

This shows that when the underlying SPMe has sufficient fidelity, fewer input breakpoints are required to reach the same level of ECM accuracy. In practice, this means reduced experimental burden without loss of confidence in the resulting model.

Temperature	C-rate							
	-5.0C	-3.0C	-1.0C	-0.5C	0.5 C	1.0C	3.0C	5.0C
0°C	43.4	64.1	70.0	71.3	27.6	39.7	59.8	58.6
5°C	34.8	54.2	71.6	62.4	29.5	37.7	53.1	49.1
10°C	35.2	47.3	64.5	60.6	20.3	26.7	36.8	29.2
15°C	41.1	34.6	42.4	43.7	12.3	12.7	14.3	17.7
20°C	41.3	45.1	64.4	47.9	11.3	13.3	19.9	20.0
25°C	43.1	37.6	43.1	45.3	11.3	8.8	11.3	17.5
30°C	46.0	30.2	25.0	18.7	12.7	9.9	11.9	25.2
40°C	52.2	39.5	50.0	36.5	14.2	11.9	18.0	34.2
50°C	56.6	40.9	34.5	31.8	17.3	16.6	26.4	42.5
60°C	52.9	35.4	34.7	16.5	20.1	20.0	34.4	58.4

Temperature	C-rate							
	-5.0C	-3.0C	-1.0C	-0.5C	0.5 C	1.0C	3.0C	5.0C
0°C	51.3	37.4	68.1	82.7	32.6	20.4	42.7	68.5
5°C	46.1	35.5	77.7	55.8	72.1	28.3	56.7	69.3
10°C	39.6	39.3	55.4	41.6	45.7	47.7	64.1	79.9
15°C	64.1	40.4	28.1	34.5	43.2	48.6	75.0	98.2
20°C	40.3	30.6	38.4	35.1	44.5	38.4	65.3	87.7
25°C	50.4	37.6	35.9	30.9	41.0	46.7	67.9	81.2
30°C	60.5	52.4	33.2	25.3	40.7	53.5	72.7	147.4
40°C	64.2	40.3	34.9	27.5	46.0	54.2	80.6	90.5
50°C	69.8	42.5	31.9	26.0	45.3	81.4	83.5	97.3
60°C	76.8	38.8	29.9	27.8	53.8	58.4	98.8	129.8

Temperature	C-rate							
	-5.0C	-3.0C	-1.0C	-0.5C	0.5 C	1.0C	3.0C	5.0C
0°C	65.9	45.7	33.3	53.0	39.3	76.7	59.8	52.1
5°C	53.8	45.8	48.3	46.5	45.9	58.9	76.0	71.3
10°C	49.1	43.3	53.9	46.1	45.0	53.8	73.4	72.3
15°C	50.9	48.5	32.7	34.3	42.0	46.9	66.8	75.0
20°C	39.2	39.5	36.1	38.8	37.4	43.5	60.5	72.6
25°C	48.5	46.2	25.7	33.6	40.9	43.2	53.7	75.9
30°C	68.2	48.9	21.0	15.1	44.6	43.8	55.6	82.5
40°C	50.0	41.1	21.5	22.4	38.5	41.4	54.5	75.4
50°C	53.9	47.4	16.2	21.5	45.5	46.8	50.8	74.6
60°C	65.0	58.9	14.9	10.7	44.3	48.0	61.2	108.0

SPMe

Breathe Model

Distilled ECM

generated from Breathe Model

ECM

empirically derived

Temperature accuracy (RMSE)

RMSE ≥ 1.5°C RMSE ≥ 1.5°C

Temperature	C-rate							
	-5.0C	-3.0C	-1.0C	-0.5C	0.5 C	1.0C	3.0C	5.0C
0°C	0.7	1.2	1.5	1.4	1.2	1.1	1.1	1.0
5°C	1.0	0.5	0.6	0.5	0.6	0.6	0.6	1.0
10°C	2.7	1.6	1.0	0.8	1.0	1.1	1.0	1.1
15°C	0.6	0.7	1.0	1.1	1.1	1.2	1.2	1.1
20°C	2.0	1.0	0.6	0.3	0.8	0.6	0.6	0.9
25°C	1.4	0.6	0.6	0.5	0.5	0.8	1.0	1.1
30°C	1.2	0.6	0.5	0.3	0.5	0.8	0.9	0.8
40°C	2.2	1.8	0.6	0.5	0.4	0.8	1.0	1.8
50°C	1.9	1.4	0.5	0.4	0.7	1.0	1.2	1.6
60°C	4.4	2.5	0.3	0.4	0.6	0.8	1.8	1.9

Temperature	C-rate							
	-5.0C	-3.0C	-1.0C	-0.5C	0.5 C	1.0C	3.0C	5.0C
0°C	2.0	1.2	1.8	1.9	1.7	1.7	1.1	0.9
5°C	2.6	1.7	0.9	0.8	0.9	0.8	0.8	0.9
10°C	4.6	3.6	1.1	0.9	0.8	1.0	2.3	1.7
15°C	2.1	1.3	1.2	1.4	1.7	1.7	0.9	1.0
20°C	4.0	2.4	1.0	0.6	0.6	0.4	0.7	1.1
25°C	3.2	1.7	0.9	0.7	0.8	0.8	0.7	1.1
30°C	3.0	1.6	0.9	0.5	0.7	0.7	0.8	0.7
40°C	4.2	2.3	0.9	0.6	0.4	0.5	0.5	1.2
50°C	4.1	1.2	1.0	0.6	0.9	1.0	0.6	0.9
60°C	7.3	3.7	0.7	0.6	0.7	0.7	0.6	0.8

Temperature	C-rate							
	-5.0C	-3.0C	-1.0C	-0.5C	0.5 C	1.0C	3.0C	5.0C
0°C	2.5	2.0	0.9	1.3	1.3	0.8	0.7	0.5
5°C	3.5	2.8	0.6	0.6	0.7	0.5	1.5	1.6
10°C	5.1	3.9	1.4	0.9	0.7	1.0	2.3	2.7
15°C	2.0	1.1	1.1	1.4	1.6	1.5	0.7	0.6
20°C	3.3	2.4	0.8	0.5	0.7	0.5	0.9	1.5
25°C	2.1	1.5	0.8	0.7	0.8	1.0	0.9	1.2
30°C	1.6	1.3	0.7	0.6	0.6	0.8	1.1	0.8
40°C	1.9	1.8	0.6	0.6	0.5	0.7	0.8	1.3
50°C	1.6	1.3	0.8	0.8	0.8	1.1	1.6	1.2
60°C	4.5	2.6	0.5	0.8	0.9	1.0	0.8	1.9

SPMe

Breathe Model

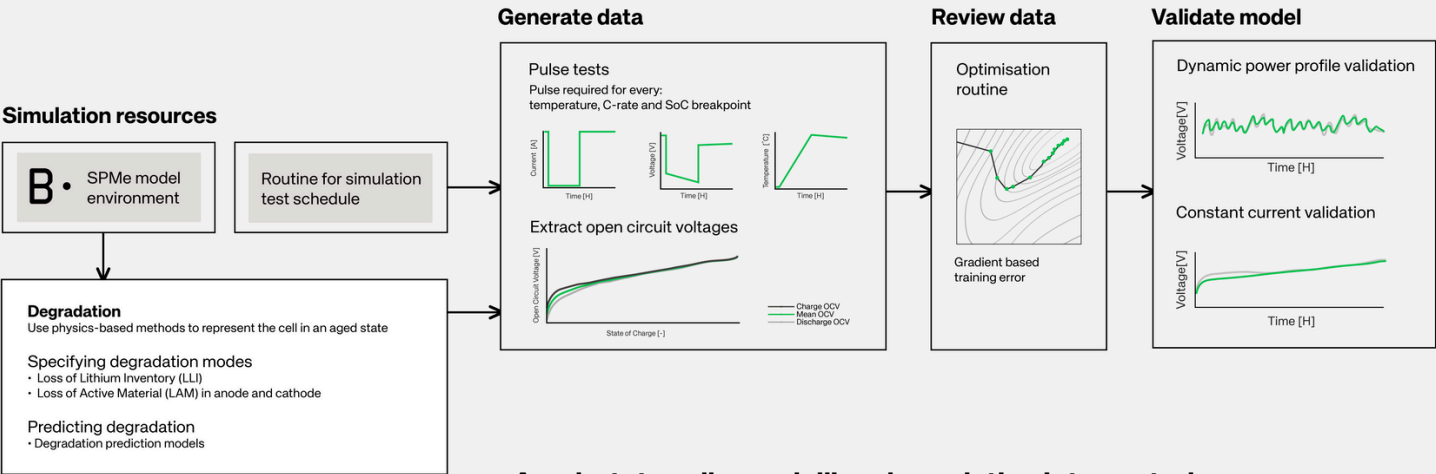
Distilled ECM

generated from Breathe Model

ECM

empirically derived

Applications:
from aged cells to new designs



Aged-state cells: modelling degradation into control

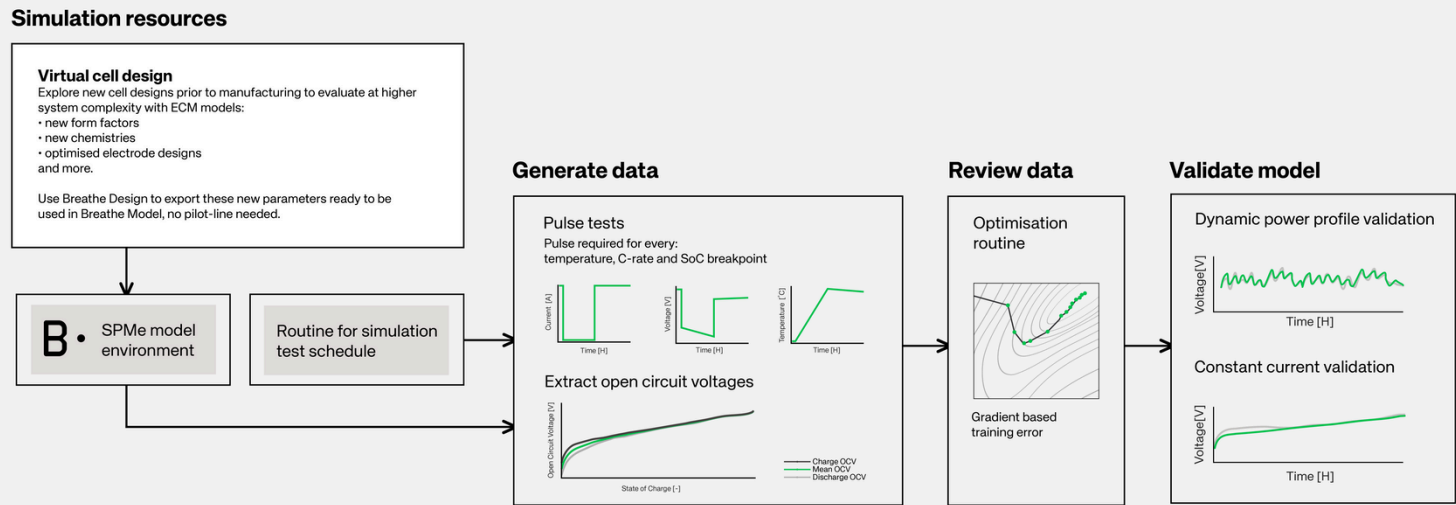
Cells evolve with use. Lithium inventory loss (LLI) and loss of active material (LAM) alter internal states, shifting both voltage response and dynamic behaviour. By specifying degradation modes, or even applying degradation models to the SPM_e before distillation, engineers can generate ECMs that embed ageing effects in a simple, usable form.

This enables controllers and system simulations to remain valid across the full lifecycle, supporting accurate state estimation, safe fast charging, and reliable end-of-life prediction. It also makes it possible to evaluate and assess system performance throughout lifetime, ensuring that performance, safety, and longevity remain suitably balanced under real-world usage conditions.

Newly designed cells: accelerating validation before production

For new designs, waiting for prototype cells slows down critical decisions. With Breathe Design, engineers can build virtual cells, run SPMc simulations, and distil ECMs directly from these prototypes. This makes it possible to evaluate fast-charging strategies, thermal management concepts, and pack-level trade-offs long before hardware is available.

At the system level, this workflow enables early assessment of vehicle or pack-level performance and safety margins before the first cells are even delivered. The result is a faster, more flexible path to design validation, where development moves forward in parallel with cell fabrication.



Conclusion and outlook: distilled ECMs as the new standard

Distillation is not just about simplification. It is about using the right tool for the job, making the complex simple, and stripping away what is unnecessary for the application in question. SPM models such as Breathe Model are already valuable for control and system development, offering electrochemical visibility that supports advanced estimation and decision-making. Distilling those same models into ECMs provides an additional option: a lighter structure that integrates seamlessly into embedded workflows.

This paper has shown how physics-based workflows can generate control-ready ECMs in minutes, replace large portions of empirical testing, and extend naturally to both aged-state and prototype cells. The outcome is a modelling approach that is accurate, scalable, and compatible with existing engineering practices.

As simulation continues to be central to battery development, distilled ECMs will become the new standard for control and validation. This shift frees up critical lab resources, allowing talent and equipment to focus on the value-driving experiments that matter most. The result is both cost saved and capability gained, with engineers able to prioritise innovation, safety margins, and performance improvements rather than routine data generation.

BREATHE DESIGN

[Click here](#) for a free trial of Breathe Design.

What if the Molicel P45B was a 4680?

Create virtual cells, instantly predict their performance, and perform dynamic simulations.

Export your new designs to Breathe Model and continue your development in Simulink.

BREATHE

TRY IT FOR YOURSELF

BREATHE MODEL

[Click here](#) for a free Molicel P45B cell instance.

Breathe's SPME Model, ready to run.

Includes the full ECM generation workflow in MATLAB.

Set degradation modes and explore ECM generation of an aged cell at the speed of software.



About Breathe

Your battery partner

Breathe is more than a battery performance company.

Since being spun out of Imperial College in 2019, our focus has been on building battery technology to accelerate sustainable electrification. Today, we provide a software toolchain for batteries that encompasses the full battery development lifecycle to enable the design, validation and optimisation of better batteries.

Our dream is that one day everyone will breathe clean air. That's why we makes batteries better.

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