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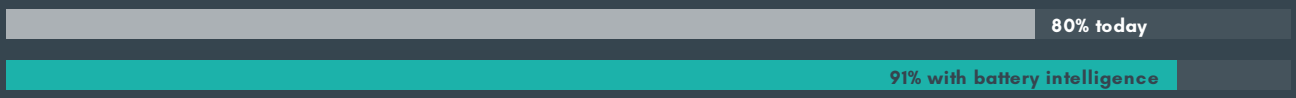
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A VELOSPUR WHITEPAPER

The capacity you **already paid for**

Physics-based battery intelligence on the BMS and a battery-aware EMS: more usable energy, longer life and safer operation from the same cells.

USABLE SHARE OF NAMEPLATE, TYPICAL LFP PROJECT, YEAR ONE



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SECTION 01

Executive summary

A battery energy storage system (BESS) is bought in megawatt-hours and run through a battery management system (BMS) that cannot see inside a single cell. The BMS measures voltage, current and surface temperature, and infers the rest. On lithium iron phosphate (LFP), the chemistry in almost every Indian BESS, that inference is hard: the voltage curve is nearly flat across most of the charge range, so a voltage reading cannot tell 40% charge from 70%.

Operators protect themselves the only way they can, with margins:

- **State-of-charge (SoC) buffers.** Wärtsilä reports that most operators hold back 10 to 15% of capacity so they never promise energy they don't have. ACCURE's fleet data shows LFP SoC errors of ±15% are common, and in one ERCOT study each point of SoC error cost 1.2% of usable capacity.
- **Stranded cells.** The weakest cell stops the whole string. In one 350 MWh system, cells had drifted 25 points of SoC apart without the BMS noticing.
- **Static limits.** Power and temperature tables written for the worst case cap the battery on its best days.
- **Overbuild.** Because ageing is uncertain, projects install extra cells upfront or plan augmentation to hold their contracted capacity.

The battery also ages faster than it needs to. Its main ageing mechanisms depend on state of charge, temperature and current, which are exactly what the energy management system (EMS) decides, usually without a model of any of them.

Physics changes both halves of the problem. Reduced-order electrochemical models running on the BMS estimate the internal states a conventional BMS cannot observe: the lithium in each electrode, the anode's potential, the cell's internal temperature. A battery-aware EMS then prices degradation into every dispatch decision. The published evidence is strong:

- In a year-long experiment, physics-based control raised trading revenue by 20% and cut degradation by 30%, lifting expected lifetime revenue by 70% (Reniers, Mulder and Howey, 2021).
- On LFP, ageing-aware operation raised lifetime profit by 29.3% over a throughput-based ageing cost (Collath et al., 2023).
- SoC- and temperature-aware dispatch extended battery life by 2.2 years, or 40% (Kumtepeli et al., 2020).

Transmission lines, transformers, wind turbines, jet engines, processors and phone batteries have all moved from static ratings to model-based ones, and each got more out of hardware already installed (Section 6).

For an Indian 100 MW / 200 MWh tender project, our worked example finds that battery intelligence cuts the cells needed to meet the contract by 13 to 20% and capital cost by about 7 to 10%. Against IEEFA and JMK Research's break-even tariff of ₹2.30 lakh per MW per month, that is worth ₹0.15 to 0.23 lakh per MW per month (Section 7).

Velospur is building this as one stack: a battery intelligence layer parameterised from our cell library, models small enough to run on the BMS, and an EMS developed in India that uses them. This paper sets out the method, the evidence, the limits, and the protocol by which we will publish our own results.

80% to 91%
usable share of nameplate, typical LFP project today and with battery intelligence

13 to 20%
fewer cells to meet a 100 MW / 200 MWh tender contract

₹2.07 to 2.15
break-even tariff in lakh per MW per month, from ₹2.30

SECTION 02

Where the capacity goes

A BESS nameplate is the sum of its cell ratings. One datasheet says so plainly: "Nominal capacity is a calculated number using the entire summation of the cells and their specified capacities" (Canadian Solar SolBank 3.0). What reaches the grid is smaller, and the gap is built from margins.

The manufacturer's window. Datasheets already separate nominal from usable energy. BYD's Cube Pro is rated 2,800 kWh but guarantees 2,590 kWh of DC usable energy at site acceptance, 92.5% (BYD, undated). Canadian Solar's SolBank 3.0 rates 4,800 kWh of DC capacity against a 5,016 kWh cell sum, 95.7%.

The uncertainty buffer. LFP's open-circuit voltage is nearly flat between about 25% and 90% SoC (Wärtsilä Energy Storage, 2025). On that plateau, 1 mV of error in the voltage-to-SoC curve can mean almost 5% of SoC error (Paizulamu et al., 2024), and LFP showed the largest charge-discharge voltage hysteresis of the chemistries Barai et al. (2015) measured, 38 mV. So the BMS counts charge, and counting drifts. What operating fleets show:

- Everoze, a technical adviser: errors of up to 5% even in advanced, well-maintained systems, corrected by periodic full charges and discharges (pv magazine, 2024).
- ACCURE, across more than 15 GWh of data: ±15% is common on LFP, with outliers above 40% (ACCURE, undated).
- Wärtsilä: most operators hold back 10 to 15% of capacity, and owners often leave as much as 20% unused as a buffer (Wärtsilä, 2025).
- Powin and Tierra Climate, modelling ERCOT: each 1% of SoC error reduced usable capacity by 1.2% (pv magazine USA, 2025).

The weakest cell. A string stops discharging when its emptiest cell reaches the lower limit, and stops charging when its fullest reaches the upper one. New LFP cells are well matched, with capacity varying by 0.28% across 1,100 cells (Rumpf et al., 2017), but the spread grows in service. One 2 MW string's SoC spread grew from 10% in July to 74% in October (TWAICE, undated). A 350 MWh European system had cells at 100% and 75% at the same time, undetected by its BMS (pv magazine, 2026a). A TWAICE customer with a 300 MWh system was losing 18 MWh a day, over $1 million a year, to uneven discharge (TWAICE, 2025). Passive balancing can only bleed energy from the fullest cells; in one comparison, active balancing gave up to 3.1% more discharge capacity and 7.7% longer service life (Ziegler et al., 2021).

Static limits. Power limits come from tables built for the worst case. When cells are cool and mid-SoC the real headroom is higher; when they are hot and full it is lower, and a table cannot tell the difference. Managing limits on internal electrochemical states rather than terminal voltage raised usable power density by 22% in one study (Smith, 2006).

Overbuild for ageing. Because fade is uncertain, developers either install 15 to 20% extra capacity upfront or plan augmentation in year 5 or 7, and one US operator expects a typical grid battery to lose 20 to 30% of its capacity in its first decade (Energy-Storage.news, 2026).

Put together, a typical LFP project delivers about 80% of its nameplate as usable energy in year one, before any ageing. That is our estimate, with assumptions in Section 7; it is also the depth of discharge IEEFA and JMK Research assume in their Indian break-even analysis (IEEFA and JMK, 2026).

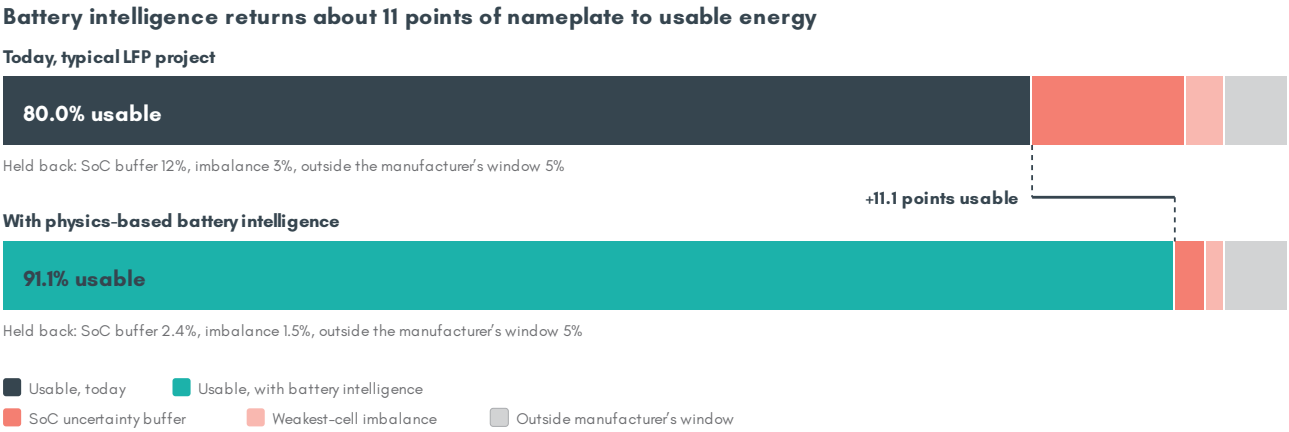


Figure 1. Share of BESS nameplate energy in year one, before ageing. Velospur estimate for a typical LFP project, from the sources in this section; assumptions in Section 7.

Each of these margins exists because the BMS cannot see the state it protects. Narrow the uncertainty and the margin can shrink, without touching the hardware limits that keep cells safe.

SECTION 03

Why batteries age faster than they need to

Capacity fade is not a fixed property of a cell. It is the sum of how the cell has been used. In LFP/graphite cells the main mechanisms are well mapped:

- **Lithium loss to the solid electrolyte interphase (SEI)**, faster at high temperature and at high SoC, where the graphite anode sits at low potential. Keil et al. (2016) found LFP calendar fade rises in a step above about 70% SoC, and advise that high storage SoC "should be avoided". In the same study fade ran at about 0.2 percentage points a month at 25 °C and 0.5 at 50 °C: roughly 2.4 against 6 points a year if sustained.
- **Lithium plating**, favoured by low temperature, high SoC and fast charging (O'Kane et al., 2022), and historically the main driver of the sudden "knee" in ageing curves (Attia et al., 2022).
- **Cycling stress** that depends on depth, rate and where in the SoC range the cycles fall. Naumann et al. (2020) observed "unexpectedly strong, but partly reversible" capacity loss from shallow cycles at medium SoC, which is exactly the micro-cycling of frequency services.

Sandia's multi-year tests found that even inside manufacturer specifications, time to 80% capacity varied "by thousands of hours and cycle counts" depending on conditions (Preger et al., 2020). Use decides life.

Most of those conditions are set by the EMS: how long the battery sits full waiting for the evening peak, how fast it charges, how deep it cycles, which racks carry the current, how hard the cooling works. A conventional EMS treats the battery as a bucket with fixed limits and, at best, a cost per MWh of throughput. A throughput cost cannot see that an hour at 95% SoC and 40 °C ages a cell far more than an hour at 50% and 25 °C.

Heat is India's multiplier. Indian sites see 45 °C ambient. One review summarises the rule of thumb that lithium-ion life halves for every 15 °C above the rated temperature (Henke and Hailu, 2020). NREL's grid-battery life model shows the trade: in its scenario, thermal management holding cells at 20 to 30 °C extended life from 4.9 to 7.0 years, and also limiting depth of discharge took it to 10 years (NMC cells; Smith et al., 2017). But cooling costs energy. In a 192 kWh LFP container, auxiliary consumption cut system efficiency by 8 to 13 percentage points in typical applications (Schimpe et al., 2018), and Indian contracts penalise round-trip efficiency below 85%. In India the cooling setpoint is a financial decision between energy and life, and only a model that knows both can make it well.

SECTION 04

What a physics-based battery intelligence layer knows

There are four ways to estimate what is happening inside a cell.

METHOD	WHAT IT SEES	ON THE LFP PLATEAU	AGEING	WHAT IT LETS THE EMS DO
Coulomb counting with voltage resets	Charge in and out	Drifts; resets need full charges or discharges	Capacity, from occasional full cycles	Run fixed SoC windows
Equivalent-circuit model with a Kalman filter	Terminal-voltage dynamics	Weak: a flat curve gives "poor observability" (Gao and Onori, 2025)	Resistance and capacity trends	Fixed windows, table-based power limits
Data-driven models trained on fleet data	Patterns in past data	Only as good as the training data	Good where history exists; weak on new cells, climates and chemistries	Alerts and forecasts
Reduced-order electrochemical model with an observer	Lithium in each electrode, electrode potentials, internal temperature, side reactions	Hysteresis and electrode balance modelled explicitly	Separates lithium loss from electrode loss; predicts plating	Dynamic windows, physics-based power limits, a degradation cost for every decision

Physics-based models descend from Doyle, Fuller and Newman's 1993 framework. Their reduced forms are compact: the single particle model with electrolyte (SPMe) tracks the full model with 3 mV RMS voltage error at 1C, against 19.9 mV for the plain single particle model, and runs an order of magnitude faster (Marquis et al., 2019). Open-source tools such as PyBaMM (Sulzer et al., 2021) make these models and their degradation submodels reproducible.

What they expose that a conventional BMS cannot:

- **Charge in each electrode**, not just in the cell, with hysteresis modelled from curves measured in both directions.

- **The anode's potential against lithium**, the variable that decides plating. An anode-overpotential observer let one team charge 96.8% of a cell's capacity in 52 minutes with no lithium deposits found afterwards (Chu et al., 2017).
- **Internal temperature**, rather than the surface reading (Klein et al., 2013).
- **Which ageing mechanism is at work**: loss of lithium inventory or loss of active material, which call for different responses.

In experiments, electrochemical observers have held SoC error below 2% (Bartlett et al., 2016, on blended lithium manganese oxide (LMO) and NMC cells) and capacity error within 2% (Allam and Onori, 2021). LFP's flat curve limits every method, ours included. The gain comes from modelling hysteresis and electrode balance explicitly and from reading the information in dynamics and rests rather than in voltage alone. We will publish our LFP error bands from field data (Section 9).

The states we estimate

STATE	WHAT IT MEANS	WHO USES IT
SoC	Charge in the cell, and in each electrode	EMS scheduling, balancing
SoE	Energy deliverable at the meter now, given temperature, power and efficiency	Dispatch and capacity tests
SoP	Charge and discharge power available over the next seconds to minutes without breaching electrochemical limits	Dispatch, power conversion system (PCS) limits
SoH	Capacity and resistance, with lithium loss and electrode loss separated	Warranty, augmentation, valuation
SoT	Internal temperature	Thermal control
SoS	Safety margin: distance to plating, abnormal self-discharge, departures from expected behaviour	Protection and alarms
RUL	Remaining useful life under the planned duty	Finance and contracts

How the models are built

Every cell type we deploy is characterised before it goes into a pack: open-circuit voltage in both the charge and discharge directions to capture hysteresis, pulse tests across the SoC range, and galvanostatic intermittent titration (GITT) at 0, 25 and 45 °C. These are the measurements a physics model needs. They become our cell library, one parameter set per cell type, refined as the fleet ages.

Why the models run on the BMS

- **Speed.** Power limits need updating every second and protection acts in milliseconds. India's amended construction standards will require, from 1 April 2027, SCADA data at 1,000 samples a second, kept for 90 days (CEA, 2026b); the place to use that resolution is next to the cells.
- **Resilience.** Across 130+ utility projects TWAICE monitors, its CEO reports that about 45% of severe incidents came from control and communication failures between the EMS and BMS (pv magazine, 2026b). A battery that carries its own model keeps accurate limits when the link drops.

- **Size.** Reduced-order electrochemical models are small. A Padé-reduced pseudo-2D model has run in real time in an electric vehicle's BMS with voltage error under 15.8 mV at −13 °C (Gao et al., 2021), and reduced-order filters use 4 to 7 states, comparable to an equivalent-circuit model (Smith, Rahn and Wang, 2010). Plett and Trimboli's 2024 text targets "reduced-complexity models that can be used on inexpensive microcontrollers" (Plett and Trimboli, 2024).

The cloud still matters: it re-identifies parameters as cells age, learns across the fleet, and keeps the compliance record. States and limits at the edge, learning in the cloud.

SECTION 05

From states to dispatch: the battery-aware EMS

An EMS that knows the cell can do six things a bucket model cannot.

01 **Price degradation into every decision.** Each candidate schedule gets a cost in lost capacity, computed from the physics model at the temperatures, SoC and currents it implies. How the cost is set matters: an optimised ageing cost beat the common practice of pricing ageing from battery system cost (Collath et al., 2023), and a depreciation proxy that did not match the revenue actually lost to ageing cut profit 30 to 50% below the best case (Kumtepeli et al., 2024).

02 **Open the SoC window only when it pays.** Rest at mid SoC, charge just before the discharge window, and use the full range on the days the schedule needs it. Because LFP calendar fade steps up above 70% SoC, time spent full is the cheapest ageing to avoid.

03 **Replace static tables with state of power.** Dispatch to the power the cells can deliver now: more in cool, mid-SoC hours, less when the model sees heat or plating risk.

04 **Run cooling to the economics.** Set the heating, ventilation and air conditioning (HVAC) hour by hour from the trade between auxiliary energy, with its efficiency penalty, and the ageing it avoids.

05 **Manage the weakest cells.** Find drifting cells and racks early, schedule balancing and SoC recalibration into low-value hours, and where the power electronics allow, let stronger strings carry more current.

06 **Keep the contract and the warranty.** Track capacity, availability and efficiency against the offtake contract, and track warranty conditions as stress-weighted equivalent cycles rather than raw throughput. DNV lists typical conditions: about one full discharge a day on average, cells near 25 °C, a fixed C-rate, and an annual average SoC below 50% (DNV). Plan augmentation from predicted fade, not assumed fade.

What the evidence says

STUDY	SETTING	RESULT
Reniers, Mulder and Howey, 2021	NMC cells, 347-day experiment, day-ahead arbitrage	Revenue up 20%, degradation down 30%; projected life from 8.2 to 11.7 years and lifetime revenue up 70%; profit forecast error cut from 170% to 13%
Reniers et al., 2018	Simulation, day-ahead arbitrage	More accurate models allowed smaller safety margins, raising revenue by up to 42%
Collath et al., 2023	LFP, intraday arbitrage, lifetime digital twin	Lifetime profit up 29.3% over a throughput-based ageing cost
Kumtepeli et al., 2020	SoC- and temperature-aware dispatch	Life up 2.2 years (40%); lifetime profitability up 25%
Maheshwari et al., 2020	NMC data, day-ahead arbitrage	Degradation down 22.7% while earning 98.8% of maximum revenue
Xu et al., 2018	Market bidding, NMC cells	With no ageing cost, life fell to 2.9 years and profit turned negative; the most detailed ageing model earned the most

Most of this evidence comes from NMC cells and arbitrage markets. LFP under Indian tender contracts is less studied, which is why Section 9 commits us to publishing our own numbers.

What today's platforms describe

Tesla says Autobidder draws on "battery system physics down to the cell level" to weigh warranties and maintenance (Tesla, undated). Fluence's Mosaic incorporates "warranty constraints and operating parameters into optimized bids" (Fluence, undated). Wärtsilä's GEMS Pulse adds analytics on available energy, imbalance and degradation (Wärtsilä, 2025), and FlexGen's health feature estimates degradation from energy flow (FlexGen, undated). In the public material we reviewed, none describes an electrochemical degradation model inside dispatch. Reniers and colleagues named what that takes: "tight coupling of the battery management system and energy management system" (Reniers, Mulder and Howey, 2021). Building both sides of that coupling is the reason for our stack.

SECTION 06

Others have made this move

Every industry that runs expensive hardware close to its limits has made the same change: from a static rating set for the worst case to a dynamic one set by a model of the asset's actual state. Each time, the same hardware delivered more.

FIELD	STATIC LIMIT	WHAT REPLACED IT	WHAT IT UNLOCKED
Transmission lines	Seasonal worst-case rating	Ambient-adjusted ratings, required hourly in the US under FERC Order 881, and dynamic line ratings	10 to 15% more capacity on average in the EU TWENTIES project (IRENA); 30 to 44% at NYPA (US DOE); over 16% at PPL (Renewable Energy World)

FIELD	STATIC LIMIT	WHAT REPLACED IT	WHAT IT UNLOCKED
Power transformers	Nameplate rating	Modelled hot-spot temperature and loss-of-life accounting (IEC 60076-7, IEEE C57.91)	7 to 10% more peak load with negligible impact on transformer life (SP Energy Networks)
Wind turbines	Generic type-class power settings	Site-specific load models and software uprates	Up to 5% more annual energy (Vestas PowerPlus; GE PowerUp), which GE put at up to 20% more profit per turbine
Jet engines	Full rated take-off thrust	Derated thrust computed for each take-off; health-monitored, per-hour service contracts	Regular 25% derate gave a near order-of-magnitude increase in cycles to failure in a GE CF6-80 study (Flight Safety Foundation); Rolls-Royce reports about 25% longer overhaul intervals under TotalCare (Rolls-Royce)
Processors	Base clock	Turbo from measured power, current and temperature headroom	An Intel Core i9-14900K runs from a 3.2 GHz base to as high as 6.0 GHz (Intel, undated)
Phone and laptop batteries	Voltage-based gauge plus a shutdown reserve	Model-based gauging (TI Impedance Track)	Peak error about 1% against 17 to 20% for voltage correlation in TI's tests (Texas Instruments, 2023)
Gas turbines	Fixed inspection intervals	Duty-weighted equivalent hours and starts (GE Vernova)	Intervals shorten for hard duty and lengthen for light duty; one part-load analysis found 9% longer intervals (Combined Cycle Journal, 2025)

India has started too: Power Grid's 400 kV Madurai to Tuticorin line now runs a dynamic line rating system (Mercom India, 2025).

Four lessons carry over to batteries:

- **The gain is large on average, not every hour.** Dynamic ratings sometimes fall below the static ones they replace (IEA, 2026); Great River Energy found its seasonal summer rating higher than the dynamic one 2 to 3% of the time. A battery's dynamic limits will sometimes be tighter than today's tables, and that is part of the value.
- **The next element becomes the limit.** At Great River Energy, dynamic rating opened 48.9% more line capacity, but the next-most-limiting element was rated 173 MVA against the line's 142 MVA, capping the usable gain at about 22% (POWER, 2025). In a BESS the PCS, transformer and cooling are the next elements; they have to be sized and controlled with the cells.
- **Life is a budget.** Transformer guides treat insulation life as something to spend deliberately: ageing doubles for about every 6 °C of hot-spot temperature (Santisteban et al., 2018), so cool hours bank life that planned overloads can spend. Battery capacity can be budgeted the same way, and the gas-turbine habit of counting stress-weighted hours is the right basis for battery warranties.
- **Guardrails are part of the design.** In 2024 Intel traced instability in some processors to an algorithm making "incorrect voltage requests" (Intel, 2024). Dynamic limits need hard protection beneath them. Our models work inside the BMS's hardware protection envelope and never replace it.

The closest precedent is in every pocket. Phones and laptops once shut down early, holding back a reserve to avoid sudden cut-offs, "leaving a significant amount of energy unused"; once model-based gauges arrived, "the battery capacity can be fully utilized" (Texas Instruments, 2007). The SoC buffer on a grid battery is the same reserve, at the scale of a power plant.

SECTION 07

What it is worth: a 200 MWh Indian tender project

Indian standalone storage is mostly bought through tenders that pay a fixed capacity charge. The contract terms decide where battery intelligence earns:

- **Capacity is tested at the meter.** MSEDCL requires three consecutive days of full-capacity charge and discharge, metered at the main availability-based tariff (ABT) meter, before commercial operation (MSEDCL, 2026).
- **Availability below 95% costs twice the capacity charge** on the shortfall in SJVN's agreement for Haryana (SJVN, 2026).
- **Round-trip efficiency must be at least 85% a month**, with penalties below it (SECI, undated; SJVN, 2026), and MSEDCL lets bidders who guarantee more than 85% lower their effective capacity charge.
- **Capacity may fade only on schedule.** SJVN's minimum dispatchable capacity falls from 97.5% in year 1 by 2.5 points a year to 70% in year 12. SECI's Kerala tender extends contracts only for the capacity still demonstrated (SECI ESS-3).
- **Tariffs sit at break-even.** GUVNL cleared at ₹2.32 lakh per MW per month in August 2026 (pv magazine India, 2026a), against IEEFA and JMK's ₹2.30 lakh break-even; most 2025 awards sit below it.
- **The EMS must be Indian.** For projects funded through viability gap funding (VGF) the EMS application software must be developed in India (SolarQuarter, Aug 2025), and it is reported to count toward the 20% local-content requirement (SolarQuarter, Dec 2025).

The worked example

A 100 MW / 200 MWh two-hour project on SJVN's capacity schedule. We compare a conservative and a typical project today with the same project run on physics-based battery intelligence.

ASSUMPTION	TODAY, CONSERVATIVE	TODAY, TYPICAL	WITH BATTERY INTELLIGENCE	BASIS
SoC error	5%	10%	2%	Everoze; ACCURE and Wärtsilä; observer studies, and ACCURE's ±2% with advanced analytics
Usable capacity lost per point of SoC error	1.2	1.2	1.2	Powin and Tierra Climate
Cell imbalance loss	2%	3%	1 to 1.5%	Ziegler et al.; field cases in Section 2. The 1 to 1.5% assumes active or EMS-scheduled balancing
Capacity fade a year	3.0%	3.0%	2.25 to 2.5%	17 to 25% less fade; published reductions run from 22.7% to 30%
Manufacturer's usable window	95%	95%	95%	BYD and Canadian Solar datasheets

In every case we assume 95% discharge efficiency from cells to meter, and a capital cost of ₹1.03 crore per contracted MWh, as in the contract NTPC awarded for its Mouda plant and terminated in September 2026 over contractor default (about ₹413 crore for 400 MWh; pv magazine India, 2026b). Only the capital-cost values in crore depend on this figure; the percentages do not. Battery enclosures are about half of a two-hour project's cost: Ember puts enclosures at close to 90% of the $75/kWh of core equipment within a $125/kWh all-in cost for four-hour projects, and the PCS weighs more at two hours (Ember, 2025). We scale the break-even tariff with capital cost, as in IEEFA and JMK's model, where O&M is a share of capex.

RESULT	CONSERVATIVE CASE	TYPICAL CASE
Usable share of nameplate, today and with battery intelligence	87.0% and 91.6%	80.0% and 91.1%
Overbuild needed to meet the capacity schedule	9.4%, then none	9.4%, then none
Cells installed, today and with battery intelligence	265 and 230 MWh	288 and 231 MWh
Cells saved	35 MWh (13%)	57 MWh (20%)
Capital cost saved	about 6.6% (₹13.6 crore)	about 9.9% (₹20.3 crore)
Break-even tariff, lakh per MW per month	from ₹2.30 to ₹2.15	from ₹2.30 to ₹2.07

Battery intelligence cuts the cells needed for a 200 MWh contract by 13 to 20%

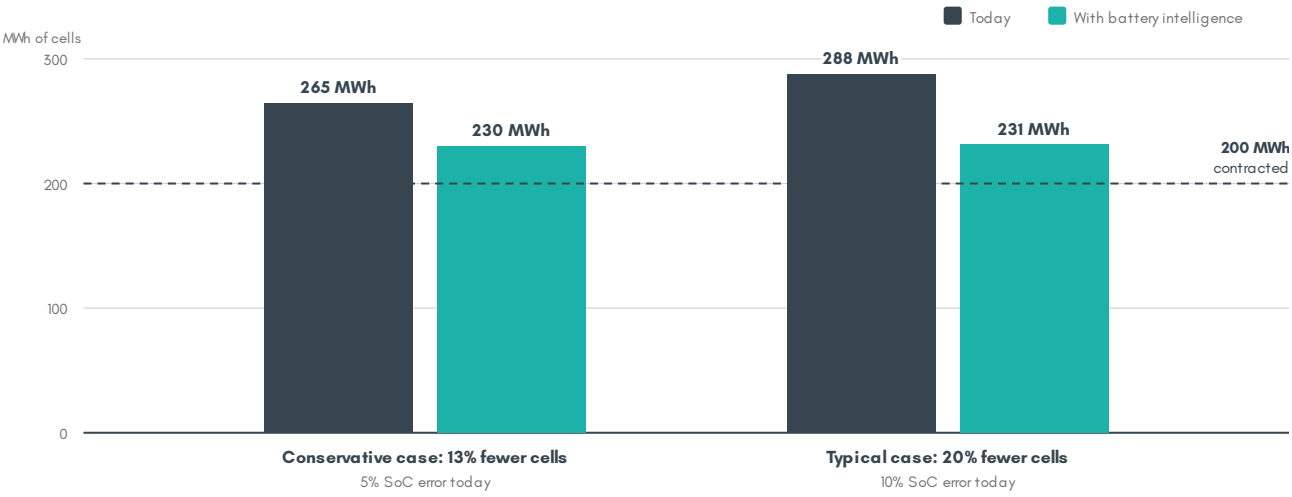


Figure 2. Cells installed to meet SJVN's capacity schedule for a 100 MW / 200 MWh two-hour project. Velospur worked example; assumptions as set out earlier in this section.

Three things stand out.

- **The fade threshold.** SJVN's schedule allows 2.5 points of fade a year. At 3% a year this project needs 9.4% more cells on day one; at 2.5% or less it needs none, and it carries surplus capacity into any extension. Each quarter-point of fade above 2.5% adds about 4.5% more cells.
- **Unit values.** On this project each point of usable window is worth about 3.6 MWh of cells, or 0.6% of capital cost. Each point of availability below 95% costs about ₹0.55 crore a year. Each point of round-trip efficiency below 85% costs about ₹0.58 crore a year, assuming 1.5 cycles a day and an average power purchase cost of ₹4.5 per unit.
- **What it does not do.** It does not rescue bids at ₹1.5 to 1.9 lakh per MW per month. It turns break-even bids into profitable ones, and lets the next bid go lower with less risk.

All figures are illustrative, built from public sources and our assumptions. A real project needs its own cell data, contract and duty cycle.

SECTION 08

The safety and compliance dividend

From 1 April 2027, India's rules ask the BMS for what physics-based estimation produces anyway:

- The Central Electricity Authority's BESS safety chapter (Chapter XA of the CEA safety regulations, in force from 1 April 2027 for installations connected above 650 V) requires the BMS to monitor and record voltage, temperature and thermal runaway at cell, module and rack level, to alarm outside the manufacturer's operating range, and to stop charging and discharging above its temperature limit (Regulation 122(B)(5)(a)). It also requires two-fault tolerance under Regulation 122(B)(2) (CEA, 2026a).
- The construction standards amendment adds state-of-health monitoring in the BMS, an RFID tag on every module naming its testing laboratory, and SCADA data at 1,000 samples a second kept for 90 days (CEA, 2026b).
- CEA's draft external safety audit format checks AC round-trip efficiency of at least 70%, auxiliary consumption included (CEA draft).

Early life is where the risk sits, and most of it lies outside the cell. Of the incidents in EPRI's failure database where system age was known, 72% happened during construction, commissioning or the first two years of operation. Only 11% of classified incidents were attributed to cells or modules, and integration, assembly and construction was the most common root cause (EPRI, TWAICE and PNNL, 2024). Factory inspections point the same way. In 2025 inspections by Intertek CEA, a quality-inspection firm unrelated to the regulator, BMS faults were the most common system-level critical safety failure, present in 4.7% of the systems inspected (ESS News, 2026), and in its 2024 factory audits 6% of systems failed capacity tests (ESS News, 2025).

A physics model gives every cell an expected behaviour. When measured voltage, temperature or self-discharge departs from it, the difference is an early signal of a cell fault, a failing sensor or an integration error, long before a fixed threshold trips. The same model produces the state-of-health record and the high-rate data trail the regulations will require.

One rule we hold to: model-based limits operate inside the hardware protection envelope and never replace it. For the two-fault tolerance Regulation 122(B)(2) requires, we count protection layers as independent only if they share no sensor, power supply, processor, firmware or switching device. A model running on the BMS adds foresight on top of the hardware layers; it is not one of them.

SECTION 09

How we will prove it

Claims about battery software are easy to make and hard to check, so we are fixing the protocol before the results:

METRIC	HOW WE MEASURE IT	COMPARED AGAINST
SoC and SoE accuracy across the LFP plateau	Estimates against reference values from controlled full discharges at the meter	The conventional BMS estimate on the same strings
Usable energy at the meter	Energy delivered per cycle inside the contracted window, in the three-day test format	Control strings, or the pre-deployment test
Capacity fade	Quarterly reference performance tests: capacity and resistance at fixed conditions	Control strings run on a conventional strategy
Round-trip efficiency	Monthly, auxiliaries included, on the contract definition	Control strings run on a conventional strategy
Availability and imbalance	Contract availability; SoC spread at the end of discharge	Control strings run on a conventional strategy
Safety signals	Lead time and false-alarm rate of model-based alerts	Fixed-threshold alarms

We will publish results from our pilots as an addendum to this paper, including where the method underperforms, with the data schema open to customers and an independent engineer's review.

SECTION 10

The Velospur stack, and what we have not solved

One stack, built in India.

- **Cells:** LFP today, sodium-ion next. Every cell type is characterised into our cell library before it goes into a pack.
- **Edge:** BMS and IoT that stream cell-level data and run reduced-order electrochemical-thermal models for SoC, SoE, SoP, SoH, SoT and SoS.
- **EMS:** dispatch, cooling, balancing, contract and warranty management, each priced with the model's degradation costs.
- **Battery intelligence:** fleet learning, parameter updates as cells age, remaining-life forecasts and the compliance record.

How to work with us.

- New BESS built on our stack.
- Our EMS and analytics on an existing system. Where we do not supply the BMS, the models run in the site controller on the BMS data stream, at lower resolution.
- Independent health validation for owners, lenders and insurers.

What we have not solved yet.

- LFP's flat curve limits observability for every method. We will publish our error bands, not just our best case.
- Models need parameters, and parameters drift as cells age. Re-identification needs good data, and ACCURE reports that 20% of systems collect only low-quality data (ACCURE, 2025).
- Wider windows can conflict with cell suppliers' warranty terms. On third-party cells we operate inside them and use the evidence to renegotiate; on our own packs we set them.
- Dynamic limits are sometimes tighter than today's tables, and the PCS, transformer or cooling can become the next limit.
- Most published value studies used NMC cells and arbitrage markets. LFP under Indian tenders needs its own evidence.
- Sodium-ion models are less mature than LFP models. We are building them alongside our sodium-ion work.

Lines, transformers and turbines have moved past worst-case ratings. Batteries can too. We are building the EMS that knows every cell, so that the capacity our customers paid for is the capacity they get, for as long as the cells can give it.

Terms used in this paper

TERM	MEANING
BESS	Battery energy storage system
BMS	Battery management system: the electronics that measure the cells and enforce their limits
EMS	Energy management system: the software that decides when, and how hard, the battery works
PCS	Power conversion system: the inverters between the battery and the grid
SoC, SoE, SoP	State of charge, state of energy and state of power (Section 4)
SoH, SoT, SoS	State of health, state of temperature and state of safety (Section 4)
RUL	Remaining useful life
LFP, NMC	Lithium iron phosphate and nickel manganese cobalt, the two main lithium-ion cathode families
SEI	Solid electrolyte interphase: the film on the anode whose growth consumes lithium
GITT	Galvanostatic intermittent titration technique: current pulses and long rests that reveal diffusion inside the electrodes
P2D, SPM, SPMe	The pseudo-two-dimensional (Doyle, Fuller and Newman) electrochemical model, the single particle model, and the single particle model with electrolyte
CEA	Central Electricity Authority, India's technical power regulator. Intertek CEA (Clean Energy Associates), cited in Section 8, is an unrelated quality-inspection firm
VGF	Viability gap funding for BESS from India's Ministry of Power
ABT meter	The availability-based tariff meter at the grid connection, used for settlement
SCADA	Supervisory control and data acquisition

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ABOUT THIS PAPER

Draft v0.1 by Velospur, October 2026. Figures from published sources are cited where they appear; the worked example in Section 7 is illustrative, built from public sources and our assumptions. Not investment advice.

This is a working draft. We would rather be challenged on the method and the numbers now than after the pilots, so write to us through velospur.com.

ABOUT VELOSPUR

Velospur builds battery energy storage in India as one stack, from the cell to the software: battery systems, cell-level electronics, an EMS developed in India, and the battery intelligence layer this paper describes. We work with LFP today and are developing sodium-ion systems for stationary storage.