

Transforming electrified railway into mechanical energy storage for electricity system decarbonization

Supplementary Information

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Supplementary Note 1. Data objects, terminology and construction

Data objects and assessment workflow

The Electrified Rail-Based Energy Storage (ERES) capacity assessment proceeds from railway timetable data to regional ERES capacity through a sequence of connected steps. First, each regional timetable defines the scheduled train services operating within a specific region and time period. Second, these services are decomposed into inter-stop train operations (ITOs), which are the basic scheduled movements used in the railway regulation model. Third, each ITO is linked to the assigned train technical parameter set and the corresponding rail line constraints, forming an ITO-level input record that contains timetable, train and line information simultaneously. Fourth, the energy-oriented regulation model uses these ITO-level input records to evaluate feasible charge and discharge power deviations under railway operating constraints. Finally, the feasible deviations are converted into ITO-level ERES units and aggregated within each regional timetable to obtain regional ERES capacity. These regional aggregates are then used for macro-level scaling and as capacity inputs to the electricity system capacity expansion model.

Supplementary Table 1. Data objects and their roles in the ERES assessment workflow.

Object	Definition	Main information	Role in assessment workflow
Regional timetable	Scheduled railway operation records in a region and time period	Train services, scheduled times and line sections	Provides the source data for ITO extraction
Inter-stop train operation	One scheduled movement from a departure stop to the next scheduled stop	Departure and arrival stops, running time, line section and train type	Serves as the basic scheduled movement for railway regulation optimization
Train technical parameters	Technical parameters of the complete train formation assigned to an ITO	Mass, rated traction power, force limits, conversion efficiencies and maximum speed	Provides train-specific constraints for each ITO
Rail line information	Operating constraints of the rail section corresponding to an ITO	Distance and speed limit	Provides line-specific constraints for each ITO
ITO-level input record	Combined timetable, train and line information for one ITO	Scheduled times, train parameters, line distance and speed limit	Provides the complete input record for evaluating feasible power and energy deviations
ITO-level ERES unit	Storage-equivalent unit derived from one ITO	Charge power, discharge power and energy capacity	Represents the storage-equivalent unit of each ITO in regional aggregation
Regional ERES aggregation	Aggregated ERES capacity from ITO-level units in a regional timetable	Power capacity and energy capacity	Provides regional ERES capacity for macro-level scaling and capacity expansion model input

ERES and ITO denote Electrified Rail-Based Energy Storage and inter-stop train operation, respectively.

Definition and counting rules of inter-stop train operations

An inter-stop train operation is defined as one scheduled train movement from a departure stop to the next scheduled stop in the timetable. The term “stop” refers to a scheduled stop in the timetable, rather than every physical station or signal point passed by the train. Intermediate stations passed without scheduled stopping do not create additional ITOs. The following counting rules are used throughout the study:

A scheduled movement from station A to the next scheduled stop B is counted as one ITO.

If a train travels from A to F and passes B, C, D and E without scheduled stopping, the movement from A to F is counted as one ITO.

If a train has a scheduled stop at B between A and F, A to B and B to F are counted as two separate ITOs.

If the same physical train subsequently appears as a return service from B to A, the return movement is counted as a separate ITO because it has its own departure time, arrival time, line section and operation-specific constraints.

These rules ensure that each ITO has a distinct departure time, arrival time, running duration, line section and train assignment. They also ensure that the regulation model is applied to movements for which the timetable and operating trajectory are well defined.

Regional timetable definition and aggregation boundary

A regional timetable prescribes the operating state of an electrified railway fleet within a specific region and time period. It determines when each ITO starts and ends and which ITOs are available for coordinated regulation during a given grid service interval. The regional timetable therefore defines the aggregation boundary for the railway regulation optimization.

The ERES capacity derived from one regional timetable is not calculated from a single train or a single average route. It is obtained by aggregating all ITO-level ERES units available within that timetable. Each regional timetable aggregate forms one data point in the macro-scale fitting between railway activity indicators and ERES capacity.

Construction of ITO-level input records

Before railway regulation optimization, each ITO is converted into an input record that combines timetable, train and line information. The train technical parameter set is assigned to each ITO according to the scheduled train type. The line section is assigned according to the departure and arrival stops of the ITO. These fields together determine the power limits, speed limits and electromechanical conversion characteristics for each scheduled movement.

Supplementary Table 2. Timetable, train and line fields used to construct each ITO-level input record.

Data source	ITO-level field	Role in ITO-level input record
Timetable	ITO identifier	Identifies the scheduled movement used as one ITO
Timetable	Departure time	Defines the start time of the scheduled movement
Timetable	Arrival time	Defines the required arrival time for the punctuality constraint
Timetable	Running duration	Defines the scheduled service time for the railway regulation model
Timetable	Departure and arrival stop	Determines the corresponding line section
Timetable	Train type	Determines the assigned train technical parameter set
Train parameter set	Mass	Determines train inertia and mechanical energy deviation
Train parameter set	Rated traction power	Defines the aggregate motor power limit of the assigned train formation
Train parameter set	Traction force	Defines the low-speed traction force limit
Train parameter set	Braking force	Defines the low-speed braking force limit
Train parameter set	Traction efficiency	Defines electrical-to-mechanical conversion during charge regulation
Train parameter set	Regenerative braking efficiency	Defines mechanical-to-electrical conversion during discharge regulation
Train parameter set	Maximum speed	Defines the train-specific operating speed limit
Line data	Distance	Defines the movement length for the scheduled trajectory
Line data	Speed limit	Defines the section-specific admissible speed limit

ITO denotes inter-stop train operation.

This mapping links train-level technical specifications to operation-level flexibility. As a result, two ITOs operated by different train formations on the same line section may have different power and energy limits, and two ITOs operated by the same train formation on different line sections may also have different feasible regulation envelopes because of different distances, speed limits and running times.

Dataset scope and exclusions

The railway-side assessment focuses on electrified mainline railways. This scope is used because mainline railways generally have longer distances and longer running durations between scheduled stops, which provide the operating window required for mechanical energy modulation. Metro and light rail systems are not included in the present parameterization or global scaling. Their short station spacing, frequent acceleration and braking cycles, dense stop patterns and different dispatch rules would require a separate operating model.

The capacity assessment only uses electricity associated with train motion when scaling ERES potential. Non-traction auxiliary electricity demand is excluded because it does not represent mechanical energy regulation of trains. The conversion from railway electricity statistics to traction-related electricity demand is described in Supplementary Method 2.

Supplementary Method 1. Railway regulation model and ERES parameterization

Physical train dynamics

Conventional models of railway operations represent each train with ordinary differential equations (ODEs)¹. For a train with position x , speed v , mass m and rotary mass coefficient γ , the longitudinal motion is described as supplementary equations (1) and (2).

$$(1 + \gamma)m \frac{dv}{dt} = f(v) - b(v) - r(v) \quad (1)$$

$$\frac{dx}{dt} = v \quad (2)$$

The traction force $f(v)$ and braking force $b(v)$ are expressed using the rated force and rated traction power limits of the train in supplementary equations (3) and (4).

$$f(v) = u_T \min\left(F_T, \frac{P_T}{v}\right) \quad (3)$$

$$b(v) = u_B \min\left(F_B, \frac{P_T}{v}\right) \quad (4)$$

where u_T and u_B are traction and braking control inputs of the train, respectively; F_T , F_B and P_T represent total rated traction force, braking force and power of all motors of the train, respectively. The train resistance is represented using the Davis equation.

$$r(v) = m(a_0 + a_1 v + a_2 v^2) \quad (5)$$

where a_0 , a_1 and a_2 are resistance coefficients. The corresponding electrical power is expressed in supplementary equation (6).

$$P_e = v \left(\frac{f(v)}{\eta_T} - b(v)\eta_B \right) \quad (6)$$

where η_T and η_B denote the traction and regenerative braking efficiencies of the traction system, respectively. Positive P_e represents electricity absorbed by the train during traction. Negative P_e represents regenerative electrical output on the train side. Whether this regenerative power can be returned to the upstream electricity system depends on the traction power interface.

The detailed dynamic model defines the feasible trajectory and power limits of each ITO, including traction and braking force limits, rated power limits, resistance, conversion efficiencies and speed constraints. Directly optimizing the train trajectories of hundreds of thousands of ITOs with these nonlinear ODEs would be computationally intractable. Therefore, the coordinated charge and discharge regulation problems are formulated using the energy-oriented model described below.

Energy-oriented representation of train operation

Although the detailed dynamic model captures the nonlinear dynamics of train motion, it is computationally prohibitive for optimizing large-scale networks. We use an energy-oriented representation to reduce the computational burden of large-scale optimization. This method has been validated to significantly reduce computational demand while maintaining accuracy².

Given a train's operating trajectory, its state can be described by the vector $\boldsymbol{\zeta} = [x, v, t]^\top$, indicating position x , speed v , and time t . To minimize operational impact, power regulation is excluded during the initial traction and final braking phases. After excluding these phases, the admissible regulation window, defined as the railway segment from the start position $x_{\text{adm},s}$ to the end position $x_{\text{adm},e}$, is the segment during which the train maintains a relatively constant cruising speed and can adjust its trajectory flexibly. Since the train's speed remains consistently positive over this interval, the time variable t in supplementary equation (1) can be replaced by position x , as expressed in supplementary equation (7).

$$(1 + \gamma)m \frac{dv}{dx} v = f(v) - b(v) - r(v) \quad (7)$$

Considering two states, $\boldsymbol{\zeta}'_0 = [x'_0, v'_0, t'_0]^\top$ and $\boldsymbol{\zeta}'_1 = [x'_1, v'_1, t'_1]^\top$, within the admissible regulation window and integrating both sides of supplementary equation (7) from x'_0 to x'_1 , the change in kinetic energy is derived in supplementary equation (8), while the mechanical energy input is expressed in supplementary equation (9).

$$\Delta E_k := \int_{x'_0}^{x'_1} (f - b - r) dx = W_T - W_B - W_r \quad (8)$$

$$W_T - W_B = \Delta E_k + W_r \quad (9)$$

where ΔE_k represents the change in kinetic energy; W_T, W_B and W_r are the work of traction force, braking force and resistance, respectively. The change in the train's kinetic energy ΔE_k solely depends on the initial and final states of the train. Since both the average speed and total distance remain constant when the beginning state $\boldsymbol{\zeta}'_0 = [x'_0, v'_0, t'_0]^\top$ and ending state $\boldsymbol{\zeta}'_1 = [x'_1, v'_1, t'_1]^\top$ are fixed, the work required to overcome the resistance W_r remains nearly unchanged as the average speed between two states is constant. Consequently, given the terminal states of the train, the mechanical energy input $W_T - W_B$ varies minimally across different running processes. Thus, from the energy consumption perspective, the train running process can be approximated using a model of constant mechanical energy consumption, thereby simplifying the complex nonlinear dynamics inherent in train kinetics.

For ITO n , let Δt_i denote the discrete time interval, where subscript i represents the i -th interval, T^n represents the set of discrete time intervals within the available operating duration of ITO n ; $\Delta P_m^{n, \Delta t_i}$ denote the deviation of mechanical power from the scheduled baseline. The energy-oriented running constraint is expressed in supplementary equation (10).

$$\sum_{\Delta t_i \in T^n} \Delta P_m^{n, \Delta t_i} \Delta t_i = 0 \quad (10)$$

This constraint requires the ITO to recover its scheduled mechanical energy state by the end of the available operating duration, similar to the energy neutrality constraint of energy storage systems.

Scheduled baseline, admissible regulation window and regulation duration

The regulation formulation distinguishes the scheduled baseline, the admissible regulation window, the regulation duration and the available operating duration. These terms are used throughout the railway-side assessment.

Supplementary Table 3. Distinction among baseline operation, admissible regulation window and regulation duration.

Term	Defined for	Meaning	Role in the model
Scheduled baseline	Each ITO	Train trajectory and power profile without ERES regulation	Reference for power and energy deviations
Admissible regulation window	Each ITO	Time interval in which the ITO can participate in ITO regulation	availability and operational acceptability
Regulation duration	Fleet regulation	Period over which the coordinated fleet sustains an aggregate power deviation	Regulation request

ERES and ITO denote Electrified Rail-Based Energy Storage and inter-stop train operation, respectively.

The admissible regulation window excludes operation intervals that are unsuitable for regulation, such as the initial acceleration and final braking phases. An ITO can participate in a regulation problem only when its admissible regulation window overlaps the regulation duration. This treatment prevents the optimization from using infeasible power deviations that would violate timetable recovery or speed constraints.

Coordinated charge and discharge regulation optimization

For each regional timetable and prescribed regulation duration, the coordinated fleet is optimized independently in the charge and discharge directions. Charging is defined as additional electricity absorption relative to the scheduled baseline. Discharging is defined as reduced net traction demand relative to the scheduled baseline or regenerative electricity returned through the railway power supply system.

The charge regulation capacity is the maximum constant aggregate electrical power increase that can be sustained over the regulation interval T_{reg} , as expressed in supplementary equation (11).

$$P_{\text{reg}}^{\text{cha}} = \max_{\Delta P_e^n(t)} \left(\min_{\forall t \in T_{\text{reg}}} \sum_{n \in N} \Delta P_e^n(t) \right) \quad (11)$$

where $\Delta P_e^n(t)$ denotes the change in electric power of ITO n at time t ; $n \in N$ denotes ITO n belonging to available ITO set N that can participate in the regulation. The discharge regulation capacity is the maximum constant aggregate electrical power decrease that can be sustained over the same interval, as given in supplementary equation (12).

$$P_{\text{reg}}^{\text{dis}} = \max_{\Delta P_e^n(t)} \left(\min_{\forall t \in T_{\text{reg}}} - \sum_{n \in N} \Delta P_e^n(t) \right) \quad (12)$$

The two optimization problems are subject to the same railway operating constraints. The cumulative mechanical energy deviation of ITO n up to time interval Δt_i is constrained by lower and upper kinetic energy bounds in supplementary equation (13).

$$\underline{E}_k^{n, \Delta t_i} \leq \sum_{\Delta t_j \in [\Delta t_s^n, \Delta t_i]} \Delta P_m^{n, \Delta t_j} \Delta t \leq \bar{E}_k^{n, \Delta t_i}, \forall \Delta t_i \in T^n \quad (13)$$

where Δt_s^n denotes the starting discrete time interval of ITO n , and the summation includes all discrete time intervals from Δt_s^n to Δt_i ; $\underline{E}_k^{n, \Delta t_i}$ and $\bar{E}_k^{n, \Delta t_i}$ denote lower and upper kinetic energy bounds to comply with speed limits, respectively. These bounds are derived from the minimum admissible speed and the line speed limit. They ensure that the regulated trajectory remains within the permissible speed range.

The mechanical power after regulation is constrained by the available traction and braking power as supplementary equation (14).

$$-P_B^{n, \Delta t_i} \leq P_m^{n, \Delta t_i} + \Delta P_m^{n, \Delta t_i} \leq P_T^{n, \Delta t_i}, \forall \Delta t_i \in T^n \quad (14)$$

where $P_m^{n, \Delta t_i}$ is the scheduled baseline mechanical power; $P_T^{n, \Delta t_i}$ and $P_B^{n, \Delta t_i}$ are the available traction and braking power limits.

The electrical and mechanical power deviations are linked through the conversion efficiencies in supplementary equation (15).

$$\Delta P_m^{n, \Delta t_i} = \begin{cases} \Delta P_e^{n, \Delta t_i} \eta_T^n, & P_e^{n, \Delta t_i} \geq 0 \\ \frac{\Delta P_e^{n, \Delta t_i}}{\eta_B^n}, & P_e^{n, \Delta t_i} < 0 \end{cases} \quad (15)$$

where $P_e^{n, \Delta t_i}$ denotes the scheduled baseline electrical power; $\Delta P_e^{n, \Delta t_i}$ denotes the deviation of electrical power from the scheduled baseline. The first branch represents traction operation, in which electrical input is converted to mechanical power. The second branch represents regenerative operation, in which mechanical braking power is converted to electrical output.

Extraction of ITO-level ERES power and energy parameters

The regulation optimization in the preceding section provides the power deviation profiles of the participating ITOs, which are used to parameterize storage-equivalent ERES units. Each ITO-level ERES unit is characterized by rated charge, discharge power and energy storage capacities.

The charge power capacity of ITO n is determined by the additional electrical power that can be absorbed without exceeding the available traction power, while the discharge power capacity is determined by the feasible reduction in net electrical demand, including traction reduction and regenerative output within the braking and conversion limits. The corresponding charge and discharge power capacities are expressed in supplementary equations (16) and (17).

$$P_{\text{unit},n}^{\text{cha}} = \frac{P_{\text{T}}^{n,\Delta t_i} - P_{\text{m}}^{n,\Delta t_i}}{\eta_{\text{T}}^n} \quad (16)$$

$$P_{\text{unit},n}^{\text{dis}} = \frac{P_{\text{m}}^{n,\Delta t_i}}{\eta_{\text{T}}^n} + P_{\text{B}}^{n,\Delta t_i} \eta_{\text{B}}^n \quad (17)$$

The energy capacity of each ITO is derived from the optimized regulation profiles over multiple prescribed regulation durations. For each regional timetable, regulation direction $d \in \{\text{cha}, \text{dis}\}$ and prescribed duration τ , the charge or discharge regulation optimization is solved first. The resulting electrical power deviation of ITO n at discretized time interval Δt_i is denoted by $\Delta P_{e,n}^{d,\tau}(\Delta t_i)$. Although the coordinated fleet is required to provide a constant aggregate power deviation during each optimization, the power contribution of an individual ITO can vary over time because of its admissible regulation window, scheduled baseline state and remaining trajectory. For each $\tau > 0$, we therefore calculate the duration-averaged electrical power deviation using supplementary equation (18).

$$\bar{P}_{\text{unit},n}^d(\tau) = \left| \frac{1}{\tau} \sum_{\Delta t_i \in T_{\text{reg}}(\tau)} \Delta P_{e,n}^{d,\tau}(\Delta t_i) \Delta t \right| \quad (18)$$

where $T_{\text{reg}}(\tau)$ denotes the set of time intervals included in the prescribed regulation duration τ , and Δt is the length of each discretized interval. The duration-averaged values define the ITO-level power–duration relationship obtained from the optimized regulation profiles. This relationship is fitted with a storage-equivalent curve consisting of a power-limited segment and an energy-limited segment. The fitted variable is the transition duration t_c . For a candidate transition duration t_c , the fitted storage-equivalent duration-averaged power is expressed in supplementary equation (19).

$$\hat{P}_{\text{unit},n}^d(\tau; t_c) = \begin{cases} P_{\text{unit},n}^d, & 0 < \tau < t_c \\ P_{\text{unit},n}^d t_c / \tau, & \tau \geq t_c \end{cases} \quad (19)$$

For short prescribed regulation durations, the fitted storage-equivalent unit is limited by $P_{\text{unit},n}^d$ and the stored mechanical-energy margin is not fully depleted. For longer regulation durations, the energy capacity becomes binding and the sustainable average power decreases with duration. The transition duration is therefore fitted by minimizing the squared deviation in the energy-limited segment, and the fitted energy capacity $E_{\text{unit},n}^d$ of ITO n in direction d is derived in supplementary equation (21).

$$t_{c,n}^{d,*} = \arg \min_{t_c \geq 0} \sum_{\tau \in \mathcal{D}_E(t_c)} [\hat{P}_{\text{unit},n}^d(\tau; t_c) - \bar{P}_{\text{unit},n}^d(\tau)]^2 \quad (20)$$

$$E_{\text{unit},n}^d = P_{\text{unit},n}^d t_{c,n}^{d,*} \quad (21)$$

where $\mathcal{D}_E(t_c) = \{\tau \in \mathcal{D}: \tau \geq t_c\}$ is the subset of prescribed regulation durations located in the energy-limited segment. The charge and discharge energy capacities are fitted independently and are combined to obtain the total ITO-level energy capacity in supplementary equation (22).

$$E_{\text{unit},n} = E_{\text{unit},n}^{\text{cha}} + E_{\text{unit},n}^{\text{dis}} \quad (22)$$

This procedure converts the ITO-level regulation profile results into a storage-equivalent ERES unit. It uses the fitted

power–duration relationship and retains ITO-level heterogeneity in regulation duration, power contribution and baseline operating state.

Aggregation from ITO-level units to regional ERES capacity

The ITO-level ERES units are aggregated within each regional timetable. For a regional timetable with ITO set N , the aggregated charge power capacity, discharge power capacity and energy capacity are represented in supplementary equations (23)–(25).

$$C_{\text{ERES}}^{\text{P,cha}} = \sum_{n \in N} p_{\text{unit},n}^{\text{cha}} \quad (23)$$

$$C_{\text{ERES}}^{\text{P,dis}} = \sum_{n \in N} p_{\text{unit},n}^{\text{dis}} \quad (24)$$

$$C_{\text{ERES}}^{\text{E}} = \sum_{n \in N} E_{\text{unit},n} \quad (25)$$

These regional timetable aggregations are used in two subsequent steps. First, they form the data points for fitting scaling relationships between railway scale indicators and ERES capacity. Second, after scaling to regional planning periods, they provide ERES capacity bounds for the capacity expansion model.

Supplementary Method 2. Scaling relationships and global ERES capacity assessment

Regional timetable aggregates used for scaling

Although the energy-oriented model is computationally efficient, assessing the ERES capacity at the national level remains a significant challenge. Such assessments require detailed, real-time operational data that are difficult to obtain and are unsuitable for future projections. We therefore develop a statistical scaling approach to enable a general assessment of ERES potential using only basic railway information. This approach also allows us to explore the relationship between railway scale and ERES potential.

The scaling analysis uses regional timetable aggregates derived from the ITO-level ERES units described in the Railway regulation model and ERES parameterization section. Each data point represents one regional timetable, rather than an individual line or ITO. For each regional timetable, all ITO-level ERES units available within the timetable are aggregated to obtain charge power capacity, discharge power capacity and energy capacity. These aggregated capacities are then paired with macro-scale railway indicators calculated from the same timetable.

For regional timetable j , the aggregated data record is expressed in supplementary equation (26).

$$(E_j^{\text{trac}}, N_j, C_j^{\text{P,cha}}, C_j^{\text{P,dis}}, C_j^{\text{E}}) \quad (26)$$

where E_j^{trac} is the traction-related equivalent annual electricity demand; N_j is the number of participating trains in the timetable; $C_j^{\text{P,cha}}$ is the aggregated charge power capacity; $C_j^{\text{P,dis}}$ is the aggregated discharge power capacity; C_j^{E} is the aggregated energy capacity. The equivalent annual electricity demand is calculated by extrapolating the observed operating pattern in the regional timetable to one year. Only traction-related electricity is used in the electricity-based scaling relationship, because auxiliary electricity demand does not directly represent mechanical energy modulation of trains.

Supplementary Table 4. Summary of the 2,688 regional timetable records.

Variable	Unit	Mean	Median	Minimum	Maximum	P5–P95
Number of participating trains	—	114	96	1	320	18–251
Traction-related equivalent annual electricity demand	TWh yr ⁻¹	1.16	0.87	4.6×10^{-3}	4.01	0.13–3.07
Charge power capacity	GW	0.57	0.47	2.9×10^{-3}	1.67	0.07–1.29
Discharge power capacity	GW	0.82	0.68	6.5×10^{-3}	2.39	0.10–1.90
Energy capacity	MWh	27.4	22.2	0.15	84.6	2.67–65.2

P5–P95 denotes the range between the 5th and 95th percentiles.

Macro-scale railway indicators

Two macro-scale indicators are used to relate railway activity to ERES capacity: the traction-related equivalent annual electricity demand and the number of participating trains.

The traction-related equivalent annual electricity demand reflects the intensity of electrically driven railway operation and is more suitable for global and future projection because railway energy statistics and long-term railway development scenarios are more consistently available than detailed future timetables. Total railway electricity demand is not used directly. Non-traction auxiliary electricity demand, including lighting, heating, cooling, compressors and other passenger or equipment services, is removed before applying the electricity-based scaling relationship. This correction is required because ERES capacity originates from the modulation of train motion and the associated conversion between electrical and mechanical energy.

The number of participating trains reflects the scale of coordinated train dispatch and provides a direct operation-based measure of how many scheduled train movements can contribute to ERES regulation within a regional timetable. It is retained to show the relationship between fleet size and aggregated ERES capacity within the available operation dataset.

The electricity-based indicator establishes a relationship between ERES capacity and the railway's overall energy demand. It is therefore used for the global ERES capacity projection. The train-count-based relationship provides a rail-dispatch perspective, allowing for an examination of how ERES potential scales with the number of coordinated trains.

Scaling coefficients, fitting metrics and regional application

For each regional timetable j , the timetable-derived capacity C_j is related to a macro-scale indicator X_j through a proportional scaling model in supplementary equation (27).

$$\hat{C}_j = \lambda X_j \quad (27)$$

where $\hat{C}_j$ represents the fitted ERES capacity; λ is the scaling coefficient; X_j denotes either the number of participating trains or the traction-related equivalent annual electricity demand. The proportional form is used because the ERES capacity should approach zero when there is no participating train operation or traction electricity activity.

For a given capacity variable and indicator, the scaling coefficient is estimated by least squares using supplementary equation (28).

$$\lambda = \frac{\sum_j X_j C_j}{\sum_j X_j^2} \quad (28)$$

The capacity variables include charge power capacity, discharge power capacity and energy capacity. Charge and discharge power capacities are fitted separately because their physical limits differ in traction and regenerative operation.

Three fitting metrics are calculated. The coefficient of determination R^2 , which characterizes the linear association between the macro-scale indicator and timetable-derived ERES capacity, is calculated using supplementary equation (29).

$$R^2 = 1 - \frac{\sum_j (C_j - \hat{C}_j)^2}{\sum_j (C_j - \bar{C})^2} \quad (29)$$

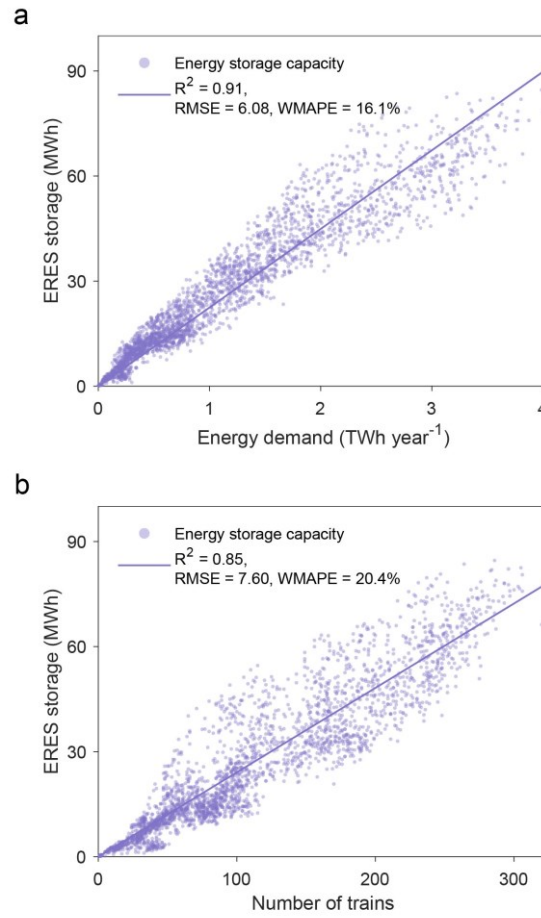
where $\bar{C}$ is the mean timetable-derived capacity. The root mean squared error, which quantifies the absolute deviation between fitted and timetable-derived values, is calculated using supplementary equation (30).

$$\text{RMSE} = \sqrt{\frac{1}{J} \sum_j (C_j - \hat{C}_j)^2} \quad (30)$$

where $J = 2,688$ is the number of regional timetables. The weighted mean absolute percentage error quantifies the normalized deviation, as defined in supplementary equation (31).

$$\text{WMAPE} = \frac{\sum_j |C_j - \hat{C}_j|}{\sum_j C_j} \times 100\% \quad (31)$$

The results are shown in Fig. 3 for power capacity and Supplementary Fig. 1 for energy storage capacity, respectively, with detailed parameters summarized in Supplementary Table 5.



Supplementary Fig. 1 | Scaling relationships for the energy capacity of Electrified Rail-Based Energy Storage (ERES). **a**, ERES energy capacity relative to the traction-related equivalent annual electricity demand of railways. **b**, ERES energy capacity relative to the number of inter-stop train operations participating in regulation. Points represent regional timetables, and solid lines show proportional fits. R^2 , RMSE and WMAPE denote the coefficient of determination, root mean squared error and weighted mean absolute percentage error, respectively.

Supplementary Table 5. Scaling coefficients and fitting deviations for ERES capacity.

Indicator	Capacity variable	λ	Unit of λ	R^2	RMSE	WMAPE
Traction-related annual electricity demand	Charge	449	MW	0.81	0.17	22.3%
	power capacity		per TWh yr ⁻¹			
	Discharge	660.1	MW	0.89	0.19	17.6%
	power capacity		per TWh yr ⁻¹			
	Energy capacity	22.45	MWh	0.91	6.08	16.1%
			per TWh yr ⁻¹			
Number of participating trains	Charge	4.922	MW	0.88	0.13	17.5%
	power capacity		per train			
	Discharge	7.161	MW	0.89	0.19	17.1%
	power capacity		per train			
	Energy capacity	0.241	MWh	0.85	7.60	20.4%
			per train			

ERES denotes Electrified Rail-Based Energy Storage. λ denotes the fitted proportional scaling coefficient. R^2 , RMSE and WMAPE denote the coefficient of determination, root mean squared error and weighted mean absolute percentage error, respectively.

To account for regional differences in fleet composition when applying the electricity-based scaling relationship, train mass and average operating speed are used as compact fleet descriptors. Train mass and speed enter the train-level mechanical-energy calculation, and their traction-electricity-weighted averages describe fleet characteristics that differ among high-speed passenger, conventional passenger and freight services³. For timetable record i and capacity variable $q \in \{P^{\text{cha}}, P^{\text{dis}}, E\}$, the capacity intensity and the two fleet descriptors are expressed in supplementary equations (32)–(34).

$$R_{i,q} = \frac{C_{i,q}}{E_i^{\text{trac}}} \quad (32)$$

$$M_i = \frac{\sum_n e_{i,n} m_{i,n}}{\sum_n e_{i,n}} \quad (33)$$

$$V_i = \frac{\sum_n e_{i,n} v_{i,n}}{\sum_n e_{i,n}} \quad (34)$$

where i indexes the timetable records and n indexes the ITOs within record i ; $C_{i,q}$ is the ERES capacity of type q , calculated using the regulation optimization and aggregation described in the Railway regulation model and ERES parameterization section; E_i^{trac} is the traction-related equivalent annual electricity demand; $R_{i,q}$ is the corresponding ERES capacity per unit of traction electricity; $e_{i,n}$, $m_{i,n}$, and $v_{i,n}$ denote the traction electricity, train mass and average operating speed of ITO n , respectively. Consequently, M_i and V_i are the traction-electricity-weighted train mass and average operating speed of timetable record i . Because mass and speed are positive quantities, their centered logarithmic descriptors are defined in supplementary equations (35)–(38).

$$\mu_M = \frac{\sum_{h=1}^J E_h^{\text{trac}} \ln M_h}{\sum_{h=1}^J E_h^{\text{trac}}}, \quad x_M(M) = \ln M - \mu_M \quad (35)$$

$$\mu_V = \frac{\sum_{h=1}^J E_h^{\text{trac}} \ln V_h}{\sum_{h=1}^J E_h^{\text{trac}}}, \quad x_V(V) = \ln V - \mu_V \quad (36)$$

$$x_{M,i} = x_M(M_i), \quad x_{V,i} = x_V(V_i) \quad (37)$$

$$x_{M,r,y} = x_M(M_{r,y}), \quad x_{V,r,y} = x_V(V_{r,y}) \quad (38)$$

where J is the number of timetable records; μ_M and μ_V are the traction-electricity-weighted log means used to center

the two descriptors. The softplus function used in the transformations below is defined in supplementary equation (39).

$$s(z) = \ln(1 + e^z) \quad (39)$$

where z is a dimensionless scalar. To represent the smooth nonlinear partial relationships between the fleet descriptors and log capacity intensity shown in Supplementary Fig. 2, the centered mass and speed descriptors are transformed using supplementary equations (40) and (41).

$$\phi_M(x_M) = 2\tau_M[\ln 2 - s(-x_M/\tau_M)] \quad (40)$$

$$\phi_V(x_V) = 2\tau_V[s(x_V/\tau_V) - \ln 2] \quad (41)$$

where $\tau_M = 0.06025$ and $\tau_V = 0.4469$ are common shape parameters shared by the three capacity variables. The $\ln 2 = s(0)$ terms center both transformations at $x_M = x_V = 0$, whereas the leading coefficient 2 gives each transformation a unit slope at that point. For each capacity variable, the response relationship is fitted using supplementary equation (42).

$$\ln R_{i,q} = \alpha_q + \gamma_{M,q}\phi_M(x_{M,i}) + \gamma_{V,q}\phi_V(x_{V,i}) + \varepsilon_{i,q} \quad (42)$$

where α_q is the response-specific intercept; $\gamma_{M,q}$ and $\gamma_{V,q}$ are the descriptor-response coefficients; $\varepsilon_{i,q}$ is the residual for timetable record i . The fitted descriptor-response coefficients used to calculate the fleet-composition adjustment term are reported in Supplementary Table 6, together with their heteroskedasticity-robust 95% confidence intervals calculated using the HC1 covariance estimator⁴. Supplementary Fig. 2 shows the corresponding partial responses and fitted curves.

For region r , year y and railway service type j , the service-specific descriptors are aggregated using their contributions to regional traction electricity demand in supplementary equations (43)–(45).

$$w_{r,y,j} = \frac{E_{r,y,j}^{\text{trac}}}{\sum_j E_{r,y,j}^{\text{trac}}} \quad (43)$$

$$M_{r,y} = \sum_j w_{r,y,j} M_{r,y,j} \quad (44)$$

$$V_{r,y} = \sum_j w_{r,y,j} V_{r,y,j} \quad (45)$$

where $E_{r,y,j}^{\text{trac}}$ is the traction electricity demand of railway service type j ; $w_{r,y,j}$ is its share of regional traction electricity demand; $M_{r,y,j}$ and $V_{r,y,j}$ are the corresponding mass and speed inputs; $M_{r,y}$ and $V_{r,y}$ are the traction-electricity-weighted regional fleet descriptors. The index j denotes high-speed passenger, conventional passenger or freight service. The mass and speed inputs are reported in Supplementary Table 7, and the traction-electricity shares are reported in Supplementary Table 8.

The regional descriptor differences and the fleet-composition adjustment term are then calculated using supplementary equations (46)–(48).

$$\Delta\phi_{M,r,y} = \phi_M(x_{M,r,y}) - \phi_M(x_{M,\text{ref}}) \quad (46)$$

$$\Delta\phi_{V,r,y} = \phi_V(x_{V,r,y}) - \phi_V(x_{V,\text{ref}}) \quad (47)$$

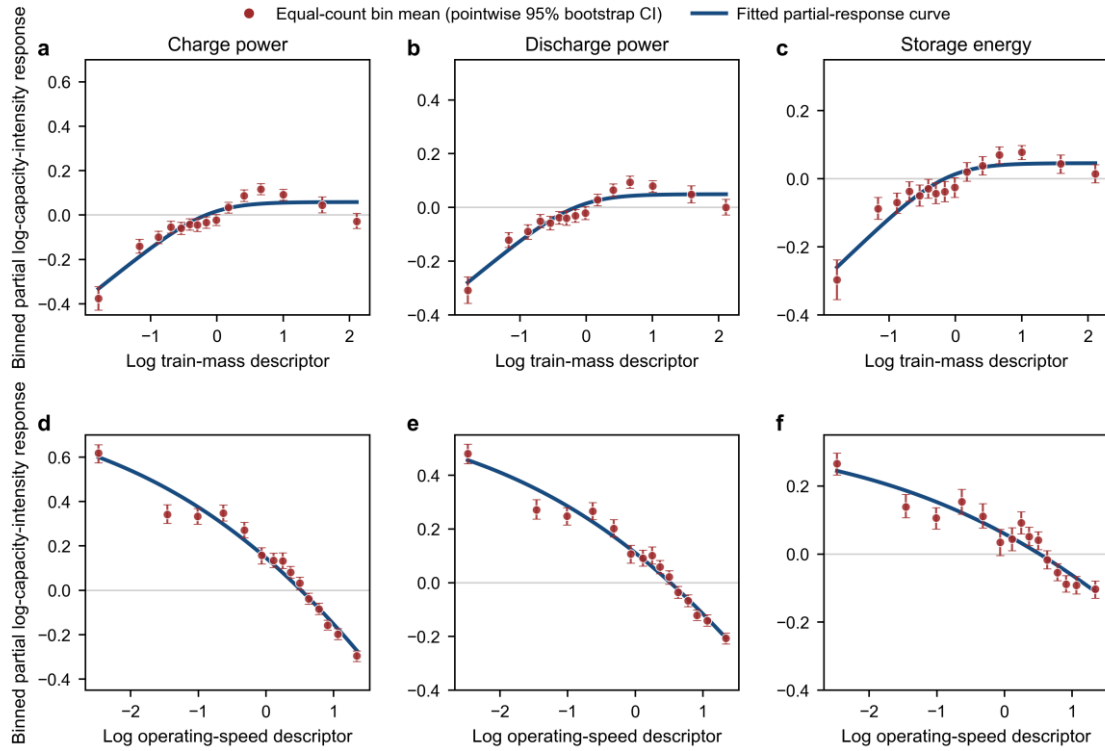
$$1 + \delta_{r,y}^q = \exp(\gamma_{M,q}\Delta\phi_{M,r,y} + \gamma_{V,q}\Delta\phi_{V,r,y}) \quad (48)$$

where ref denotes the China 2025 reference case and $\delta_{r,y}^q$ is the dimensionless region- and year-specific fleet-composition adjustment term for capacity variable q . The resulting adjustment terms are reported in Supplementary Table 9.

Supplementary Table 6. Fitted descriptor-response coefficients for the fleet-composition adjustment term.

Capacity variable	$\gamma_{M,q}$	$\gamma_{V,q}$
Charge power	0.7008 (0.6192, 0.7823)	-1.3962 (-1.4468, -1.3457)
Discharge power	0.5895 (0.5102, 0.6688)	-1.0620 (-1.1075, -1.0165)
Storage energy	0.5482 (0.4620, 0.6344)	-0.5688 (-0.6178, -0.5198)

$\gamma_{M,q}$ and $\gamma_{V,q}$ denote the fitted mass- and speed-response coefficients for capacity variable q , respectively. Values in parentheses are heteroskedasticity-robust 95% confidence intervals calculated using the HC1 covariance estimator. HC1 denotes the heteroskedasticity-consistent covariance estimator with a finite-sample correction.



Supplementary Fig. 2 | Partial relationships between Electrified Rail-Based Energy Storage capacity intensity and fleet descriptors. a–c, Partial log-capacity-intensity responses of charge power, discharge power and storage energy with respect to train mass after accounting for operating speed. d–f, Corresponding responses with respect to operating speed after accounting for train mass. Points show mean partial responses in 15 equal-count bins. Error bars denote pointwise 95% case-bootstrap confidence intervals (CIs) of the bin means. Curves show the fitted relationships.

Supplementary Table 7. Train mass and operating speed inputs by region and railway service type.

Region	High-speed	Conventional passenger	Freight
Train mass (t)			
China	650 ⁵	1060 ⁶	3548 ⁷
Europe	450 ⁸	350 ⁸	1000 ⁹
India	508 ¹⁰	1200 ¹¹	3025 ¹²
Japan	620 ⁵	318 ¹³	1400 ¹⁴
Russia	670 ⁵	1020 ¹⁵	4058 ¹⁶
Other countries	612	669	3412
Operating speed (km h⁻¹)			
China	250 ¹⁷	65.2 ¹⁸	35.6 ¹⁹
Europe	142 ²⁰	60 ²¹	30 ²²
India	254 ²³	49 ²³	23 ²³
Japan	220 ²⁴	75 ²⁵	80 ²⁶
Russia	182.2 ¹⁵	59 ¹⁵	39.7 ¹⁶
Other countries	229.1	60.3	34.8

The listed values are applied to 2025–2050. For other countries, values are derived as traction-electricity-weighted averages of the corresponding inputs for the five individually represented main railway regions.

Supplementary Table 8. Regional traction-electricity shares by railway service type.

Region	2025	2030	2040	2050
High-speed passenger				
China	0.245	0.251	0.246	0.242
Europe	0.137	0.146	0.133	0.123
India	0.009	0.011	0.008	0.006
Japan	0.156	0.172	0.212	0.258
Russia	0	0	0	0
Other countries	0.157	0.183	0.183	0.184
Conventional passenger				
China	0.072	0.063	0.063	0.063
Europe	0.628	0.628	0.66	0.683
India	0.389	0.399	0.466	0.502
Japan	0.796	0.772	0.713	0.645
Russia	0.13	0.127	0.124	0.123
Other countries	0.297	0.274	0.276	0.277
Freight				
China	0.683	0.685	0.691	0.695
Europe	0.236	0.226	0.207	0.194
India	0.602	0.59	0.526	0.491
Japan	0.048	0.056	0.075	0.097
Russia	0.87	0.873	0.876	0.877
Other countries	0.546	0.543	0.541	0.539

Shares are calculated by normalizing the high-speed passenger, conventional passenger and freight electric-rail energy-demand components reported by the International Energy Agency (IEA)²³ within each region and year. For other countries, total demand is obtained as the difference between the IEA world total and the five individually represented main railway regions. The 2025 and 2040 components are obtained by linear interpolation between the corresponding reported years before normalization.

Supplementary Table 9. Region- and year-specific fleet-composition adjustment terms.

Region	2025	2030	2040	2050
Charge power capacity				
China	0.000	-0.005	0.001	0.005
Europe	-0.273	-0.286	-0.311	-0.329
India	0.208	0.206	0.204	0.203
Japan	-0.536	-0.521	-0.487	-0.450
Russia	0.191	0.191	0.191	0.191
Other countries	0.081	0.061	0.062	0.061
Discharge power capacity				
China	0.000	-0.004	0.001	0.004
Europe	-0.242	-0.253	-0.276	-0.292
India	0.154	0.153	0.152	0.151
Japan	-0.474	-0.459	-0.425	-0.389
Russia	0.142	0.142	0.142	0.142
Other countries	0.061	0.046	0.047	0.046
Energy storage capacity				
China	0.000	-0.002	0.000	0.002
Europe	-0.253	-0.262	-0.283	-0.298
India	0.080	0.079	0.079	0.078
Japan	-0.444	-0.427	-0.388	-0.344
Russia	0.074	0.074	0.074	0.074
Other countries	0.032	0.024	0.025	0.025

Values are dimensionless adjustment terms defined in supplementary equation (48) and enter the capacity calculations through $1 + \delta_{r,y}^q$. Positive and negative values indicate upward and downward adjustments, respectively.

Conversion from railway energy projections to ERES capacity

Future global ERES capacity is estimated using railway electricity demand projections under the IEA rail development pathways²³. The projections can be converted into ERES power and energy capacities through the fitted scaling coefficients.

For region r , year y and rail development pathway s , the reported railway electricity demand in million tonnes of oil equivalent is first converted into annual electricity demand in TWh yr^{-1} using supplementary equation (49).

$$E_{r,y,s}^{\text{elec}} = 11.63 E_{r,y,s}^{\text{Mtoe}} \quad (49)$$

where 1 Mtoe = 11.63 TWh. The converted electricity demand is then partitioned by electrification type k , and the corresponding traction-related annual electricity demand is obtained using supplementary equation (50).

$$E_{r,y,s,k}^{\text{trac}} = (1 - \beta_{\text{aux},k}) \omega_{r,y,k} E_{r,y,s}^{\text{elec}} \quad (50)$$

where k denotes alternating current (AC) or direct current (DC) electrification; $\omega_{r,y,k}$ is the share assigned to electrification type k in the regional AC/DC composition; and $\beta_{\text{aux},k}$ is the corresponding auxiliary-load allocation parameter. The central auxiliary-load values of 9.3% for AC and 17% for DC are reported in a European technical assessment²⁷ and used across regions according to traction-supply type. The modeled mainline railways in China and India are represented as AC systems, whereas the European AC/DC composition is based on official European Union Agency for Railways (ERA) electrification-system statistics. The complete regional inputs are summarized in Supplementary Tables 10 and 11.

The projected ERES charge power, discharge power and energy capacities of each electrification type are then estimated using supplementary equations (51)–(53).

$$\hat{C}_{r,y,s,k}^{\text{P,cha}} = (1 + \delta_{r,y}^{\text{P,cha}}) \lambda_{\text{elec}}^{\text{P,cha}} E_{r,y,s,k}^{\text{trac}} \quad (51)$$

$$\hat{C}_{r,y,s,k}^{\text{P,dis}} = (1 + \delta_{r,y}^{\text{P,dis}}) \lambda_{\text{elec}}^{\text{P,dis}} E_{r,y,s,k}^{\text{trac}} \quad (52)$$

$$\hat{C}_{r,y,s,k}^{\text{E}} = (1 + \delta_{r,y}^{\text{E}}) \lambda_{\text{elec}}^{\text{E}} E_{r,y,s,k}^{\text{trac}} \quad (53)$$

where $\hat{C}_{r,y,s,k}^{\text{P,cha}}$, $\hat{C}_{r,y,s,k}^{\text{P,dis}}$, and $\hat{C}_{r,y,s,k}^{\text{E}}$ denote projected ERES charge power, discharge power and energy capacity, respectively; $\lambda_{\text{elec}}^{\text{P,cha}}$, $\lambda_{\text{elec}}^{\text{P,dis}}$, and $\lambda_{\text{elec}}^{\text{E}}$ are the fitted electricity-based scaling coefficients reported in Supplementary Table 5; $\delta_{r,y}^{\text{P,cha}}$, $\delta_{r,y}^{\text{P,dis}}$, and $\delta_{r,y}^{\text{E}}$ are the corresponding fleet-composition adjustment terms defined in the Scaling coefficients, fitting metrics and regional application section. For each capacity variable q , the regional capacity is obtained by summing the corresponding AC and DC components in supplementary equation (54).

$$\hat{C}_{r,y,s}^q = \sum_{k \in \{\text{AC}, \text{DC}\}} \hat{C}_{r,y,s,k}^q \quad (54)$$

The global ERES power potential reported in the main text is based on the discharge power capacity, as installed storage power capacity is conventionally interpreted as deliverable output power. For the capacity expansion model, both discharge and charge capacity bounds are incorporated in the model.

Supplementary Table 10. Regional AC/DC composition used in the Electrified Rail-Based Energy Storage capacity assessment.

Region	AC share	DC share
China ²⁸	1	0
Europe ²⁹	0.626	0.374
India ³⁰	1	0
Japan ³¹	0.39	0.61
Russia ³²	0.578	0.422
Other countries ³³	0.701	0.299

AC and DC denote alternating current and direct current, respectively. The AC and DC shares are applied to all modeled years.

We collect annual electricity consumption data for railways in countries and regions with large-scale electrified rail systems (Supplementary Table 11). Data for China, Europe, India, Japan, Russia, and the global total are obtained from the International Energy Agency (IEA)²³. Data for European Union countries and the United Kingdom are sourced from Eurostat³⁴ and the UK Department for Energy Security & Net Zero³⁵, respectively. Future rail development projections are based on IEA scenarios.

Supplementary Table 11. Energy consumption of electrified railways.

Countries and regions	Annual electricity consumption (TWh yr ⁻¹)						
	Base rail scenario				High rail scenario		
	2025	2030	2040	2050	2030	2040	2050
World	332.85	374.13	456.69	539.25	545.26	759.46	973.66
Europe	57.94	63.83	76.53	89.24	74	93.6	113.21
Austria	1.55	1.71	2.05	2.39	1.98	2.51	3.04
Belgium	1.32	1.45	1.74	2.03	1.68	2.13	2.57
Bulgaria	0.35	0.39	0.47	0.54	0.45	0.57	0.69
China	123.58	154.3	187.47	220.64	180.78	262.59	344.41
Croatia	0.02	0.02	0.02	0.03	0.02	0.03	0.03
Czechia	1.37	1.51	1.81	2.11	1.75	2.22	2.68
Denmark	0.36	0.4	0.48	0.56	0.46	0.59	0.71
Estonia	0.01	0.01	0.02	0.02	0.02	0.02	0.03
France	7.41	8.17	9.79	11.42	9.47	11.98	14.48
Germany	11.24	12.39	14.85	17.32	14.36	18.16	21.97
Hungary	1.07	1.18	1.41	1.64	1.36	1.73	2.09
India	38.21	49.02	69.62	90.23	79.63	124.8	169.97
Italy	5.57	6.13	7.35	8.58	7.11	8.99	10.88
Japan	25.47	24.9	23.19	21.47	27.78	28.85	28.85
Latvia	0.05	0.05	0.06	0.07	0.06	0.07	0.09
Lithuania	0.01	0.02	0.02	0.02	0.02	0.02	0.03
Luxembourg	0.14	0.16	0.19	0.22	0.18	0.23	0.28
Montenegro	0.01	0.01	0.02	0.02	0.02	0.02	0.03
Netherlands	1.67	1.84	2.2	2.57	2.13	2.69	3.26
Norway	0.62	0.69	0.82	0.96	0.8	1.01	1.22
Poland	2.91	3.2	3.84	4.48	3.71	4.7	5.68
Portugal	0.33	0.37	0.44	0.51	0.43	0.54	0.65
Romania	0.73	0.81	0.97	1.13	0.94	1.18	1.43
Russia	50.77	56.23	72.3	88.37	64.34	81.49	98.65
Slovakia	0.49	0.54	0.65	0.76	0.63	0.79	0.96
Slovenia	0.26	0.28	0.34	0.4	0.33	0.42	0.5
Spain	2.57	2.83	3.39	3.96	3.28	4.15	5.02
Sweden	2.54	2.8	3.36	3.92	3.25	4.11	4.97
U.K.	4.06	4.47	5.36	6.25	5.18	6.56	7.93

Global and regional ERES capacity projections

Supplementary Table 12. Electrified Rail-Based Energy Storage (ERES) power capacity of electrified railways.

Countries and regions	ERES power capacity (MW)						
	Base rail scenario				High rail scenario		
	2025	2030	2040	2050	2030	2040	2050
World	189,748	214,003	264,538	315,016	318,258	448,512	579,068
Europe	25,446	27,625	32,138	36,652	32,028	39,306	46,494
Austria	682	741	862	983	859	1,054	1,247
Belgium	578	627	730	832	727	892	1,056
Bulgaria	155	168	195	223	195	239	283
China	73,987	92,036	112,318	132,597	107,831	157,327	206,978
Croatia	7	8	9	11	9	11	14
Czechia	602	654	761	868	758	930	1,101
Denmark	160	173	202	230	201	247	292
Estonia	6	6	7	8	7	9	11
France	3,256	3,535	4,112	4,690	4,098	5,029	5,949
Germany	4,938	5,361	6,237	7,112	6,215	7,628	9,022
Hungary	469	509	592	676	590	725	857
India	26,407	33,842	47,998	62,152	54,974	86,036	117,082
Italy	2,445	2,655	3,088	3,522	3,078	3,777	4,468
Japan	7,599	7,642	7,562	7,450	8,526	9,410	10,010
Latvia	20	22	25	29	25	31	36
Lithuania	6	6	8	9	8	9	11
Luxembourg	62	67	79	90	78	96	114
Montenegro	6	6	7	8	7	9	11
Netherlands	733	795	925	1,055	922	1,132	1,339
Norway	274	297	346	394	344	423	500
Poland	1,277	1,387	1,613	1,840	1,608	1,973	2,334
Portugal	147	159	185	211	185	227	268
Romania	322	349	406	463	405	497	588
Russia	33,473	37,078	47,678	58,278	42,420	53,738	65,056
Slovakia	216	234	272	311	271	333	394
Slovenia	113	123	143	163	142	175	207
Spain	1,128	1,225	1,425	1,625	1,420	1,742	2,061
Sweden	1,117	1,213	1,411	1,609	1,406	1,726	2,042
U.K.	1,783	1,935	2,252	2,568	2,244	2,754	3,257

Supplementary Table 13. Electrified Rail-Based Energy Storage (ERES) energy storage capacity of electrified railways.

Countries and regions	ERES storage capacity (MWh)						
	Base rail scenario				High rail scenario		
	2025	2030	2040	2050	2030	2040	2050
World	6,309.23	7,127.93	8,788.73	10,448.42	10,577.76	14,891.00	19,214.34
Europe	853.42	928.46	1,081.82	1,235.15	1,076.47	1,323.11	1,566.85
Austria	22.89	24.90	29.01	33.12	28.87	35.48	42.02
Belgium	19.38	21.08	24.56	28.04	24.44	30.04	35.58
Bulgaria	5.19	5.65	6.58	7.51	6.55	8.05	9.53
China	2,516.30	3,135.58	3,818.69	4,501.75	3,673.70	5,348.95	7,027.01
Croatia	0.25	0.27	0.31	0.36	0.31	0.38	0.46
Czechia	20.20	21.98	25.61	29.24	25.48	31.32	37.09
Denmark	5.36	5.83	6.79	7.76	6.76	8.31	9.84
Estonia	0.20	0.21	0.25	0.28	0.25	0.30	0.36
France	109.20	118.80	138.42	158.04	137.73	169.29	200.48
Germany	165.61	180.17	209.93	239.69	208.89	256.76	304.05
Hungary	15.73	17.11	19.94	22.77	19.84	24.39	28.88
India	840.15	1,077.29	1,528.91	1,980.52	1,749.96	2,740.55	3,730.89
Italy	82.01	89.22	103.96	118.69	103.44	127.14	150.57
Japan	273.47	275.54	274.15	272.10	307.39	341.15	365.61
Latvia	0.67	0.73	0.85	0.97	0.84	1.04	1.23
Lithuania	0.20	0.22	0.25	0.29	0.25	0.31	0.37
Luxembourg	2.08	2.27	2.64	3.02	2.63	3.23	3.83
Montenegro	0.19	0.21	0.25	0.28	0.25	0.30	0.36
Netherlands	24.57	26.73	31.14	35.56	30.99	38.09	45.11
Norway	9.18	9.98	11.63	13.28	11.57	14.22	16.85
Poland	42.84	46.61	54.31	62.01	54.04	66.42	78.66
Portugal	4.92	5.35	6.24	7.12	6.21	7.63	9.04
Romania	10.79	11.74	13.68	15.62	13.61	16.73	19.81
Russia	1,070.28	1,185.51	1,524.35	1,863.20	1,356.30	1,718.11	2,079.92
Slovakia	7.23	7.87	9.17	10.47	9.12	11.21	13.28
Slovenia	3.79	4.13	4.81	5.49	4.79	5.88	6.97
Spain	37.83	41.16	47.96	54.75	47.72	58.65	69.46
Sweden	37.48	40.77	47.51	54.24	47.27	58.10	68.81
U.K.	59.79	65.05	75.79	86.54	75.42	92.70	109.78

Sensitivity of projected ERES capacities with respect to the auxiliary-load allocation parameter

Published studies and technical reports on electrified mainline railways provide auxiliary-load shares ranging from 6.5% to 20%^{27,36–42}. The two endpoints define the lower and upper auxiliary-load cases in the sensitivity analysis.

The central case retains the auxiliary-load allocation parameters defined in the Conversion from railway energy projections to ERES capacity section. The three cases used in the capacity sensitivity analysis are summarized in Supplementary Table 14.

Supplementary Table 14. Auxiliary-load allocation cases used in the Electrified Rail-Based Energy Storage capacity sensitivity analysis.

Case	$\beta_{\text{aux},\text{AC}}$ (%)	$\beta_{\text{aux},\text{DC}}$ (%)
Lower auxiliary-load case ³⁷	6.5	6.5
Central case ²⁷	9.3	17
Upper auxiliary-load case ⁴²	20	20

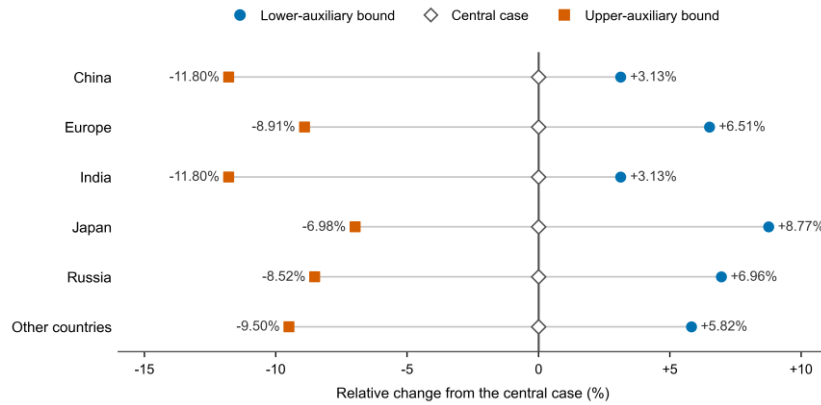
AC and DC denote alternating current and direct current, respectively. $\beta_{\text{aux},\text{AC}}$ and $\beta_{\text{aux},\text{DC}}$ denote the auxiliary-load allocation parameters for AC and DC systems, respectively.

In each auxiliary-load sensitivity case, the corresponding endpoint is applied simultaneously to the AC and DC components. Regional electricity demand, AC/DC composition, fitted scaling coefficients and fleet-composition adjustment terms remain unchanged. For region r , capacity variable q and auxiliary-load sensitivity case b , the relative change from the central case is calculated using supplementary equation (55).

$$\Delta C_{q,r}^{(b)} = \frac{C_{q,r}^{(b)} - C_{q,r}^{\text{central}}}{C_{q,r}^{\text{central}}} \times 100\% \quad (55)$$

Across the six regions, the projected ERES capacities are 3.13–8.77% higher in the lower auxiliary-load case and 6.98–11.80% lower in the upper auxiliary-load case than in the central case, as shown in Supplementary Fig. 3. Within each region, these relative changes are identical across the modeled years, railway development pathways and the three capacity variables because the auxiliary-load correction enters the corresponding AC/DC component calculations multiplicatively while the remaining inputs are fixed.

At the global level, the central-case discharge power capacities are 190 GW in 2025, 315 GW in the 2050 base pathway and 579 GW in the 2050 high-rail pathway. The corresponding estimates are 199, 329 and 605 GW in the lower auxiliary-load case and 170, 282 and 518 GW in the upper auxiliary-load case, respectively.



Supplementary Fig. 3 | Sensitivity of regional Electrified Rail-Based Energy Storage capacity estimates with respect to the auxiliary-load allocation parameter. Relative changes in the lower and upper auxiliary-load cases are calculated relative to the central case. Each row represents one modeled region. Filled markers show the two sensitivity cases, open markers at zero denote the central case, and connecting lines indicate the resulting sensitivity interval. Regional electricity demand, AC/DC composition, fitted scaling coefficients and fleet-composition adjustment terms remain fixed. AC and DC denote alternating current and direct current, respectively.

Interpretation of scaling results and projection limits

The scaling relationships are used to convert regional-timetable-based ERES assessments into macro-level capacity projections. Several limits should be considered. First, future railway timetables are not explicitly projected. The global capacity estimates therefore represent aggregated planning-level potential rather than detailed operating forecasts. Second, the electricity-based projection assumes that the relationship between traction activity and ERES capacity observed in the timetable dataset remains applicable to future electrified mainline railway activity. Third, local traction power supply constraints, reverse power flow capability, voltage limits, protection settings and grid connection feasibility are not represented in the scaling step. These issues need to be evaluated through local traction power and grid studies before deployment on specific railway lines.

Supplementary Method 3. Capacity expansion model and scenario design

Capacity expansion model and paired comparison design

This study uses version 2.0.9 of the open-source SWITCH capacity expansion model⁴³ to optimize investments and operations for generation, transmission, and energy storage to meet the electrical energy demand. He et al.^{44,45} extended the model by incorporating the energy decarbonization of electricity systems into the optimization framework, making it more suitable for simulating future sustainable energy transitions across diverse scenarios.

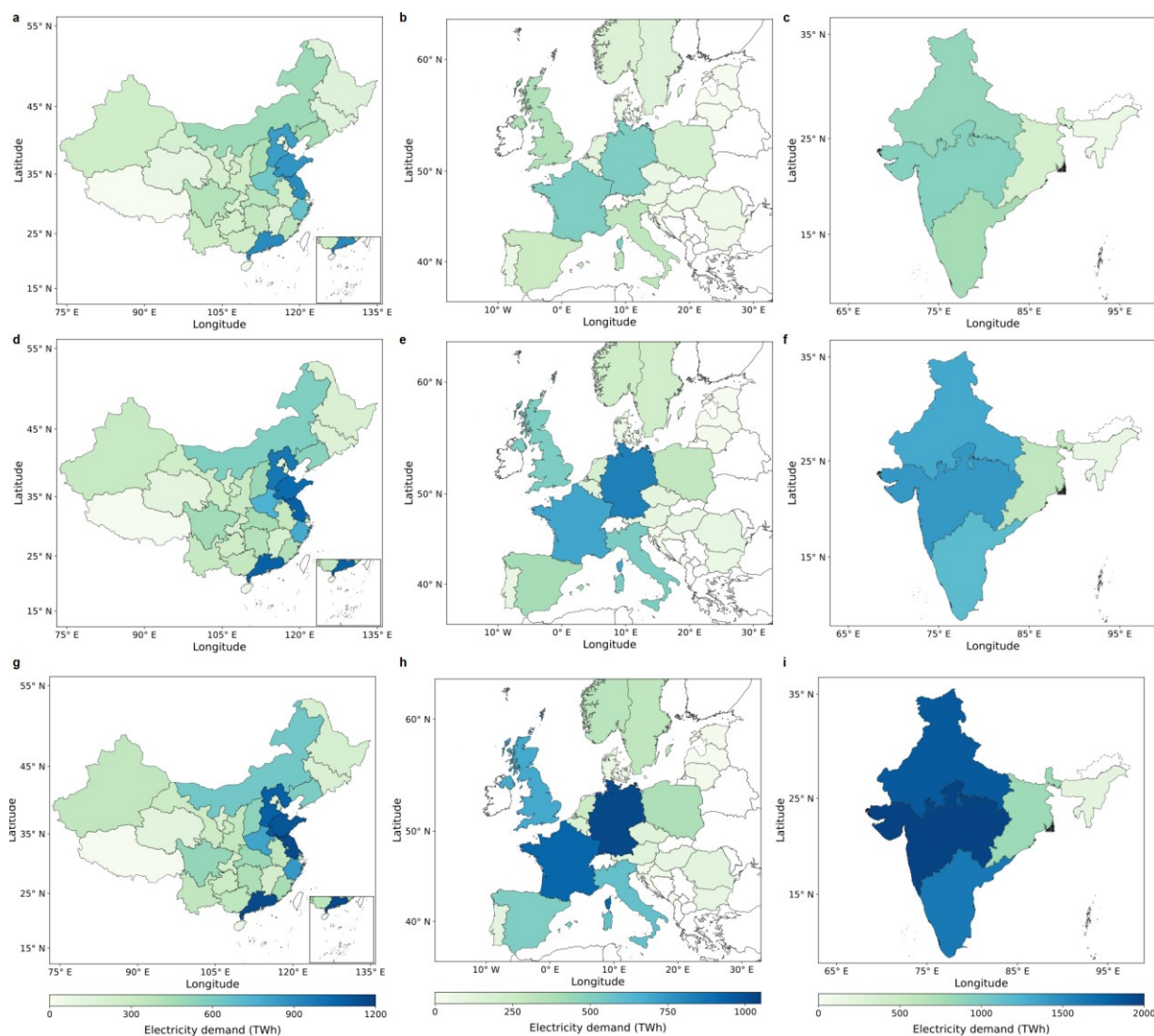
The model's objective function is to minimize the total system cost, including: capital costs of new power plants, transmission lines and energy storage; operation and maintenance (O&M) costs of existing and new power plants, transmission lines and energy storage; variable costs incurred by power plants, e.g., fuel costs and emission costs. All costs are discounted to their net present value (NPV) at a 5% rate.

To capture both short-term operation and long-term investment dynamics of electricity systems, we employ three levels of temporal resolution over the 30-year decarbonization horizon. The 1-hour time step is adopted as the basic resolution to simulate electricity system operation. This high temporal resolution enhances model accuracy by better capturing the variability of renewable energy sources, thereby enabling more precise characterization of future decarbonized electricity system dynamics and flexibility requirements. For investment planning, we adopt three decadal periods: 2025-2034, 2035-2044, and 2045-2054, represented by the years 2030, 2040, and 2050. To manage computational complexity while capturing seasonal variability, we employ four seasonal representative days for each investment period, including the median day of capacity factors for solar and wind power generation, and average load profiles. This hierarchical temporal resolution approach significantly reduces computational and memory requirements to an acceptable level. To ensure reliability during extreme conditions not captured by representative days, we enforce the peak demand reserve constraints for each period. The system must satisfy corresponding capacity reserve constraints to guarantee operational reliability. All model instances are solved using Gurobi, a commercial optimization solver, with the barrier method and a convergence tolerance of 10^{-4} .

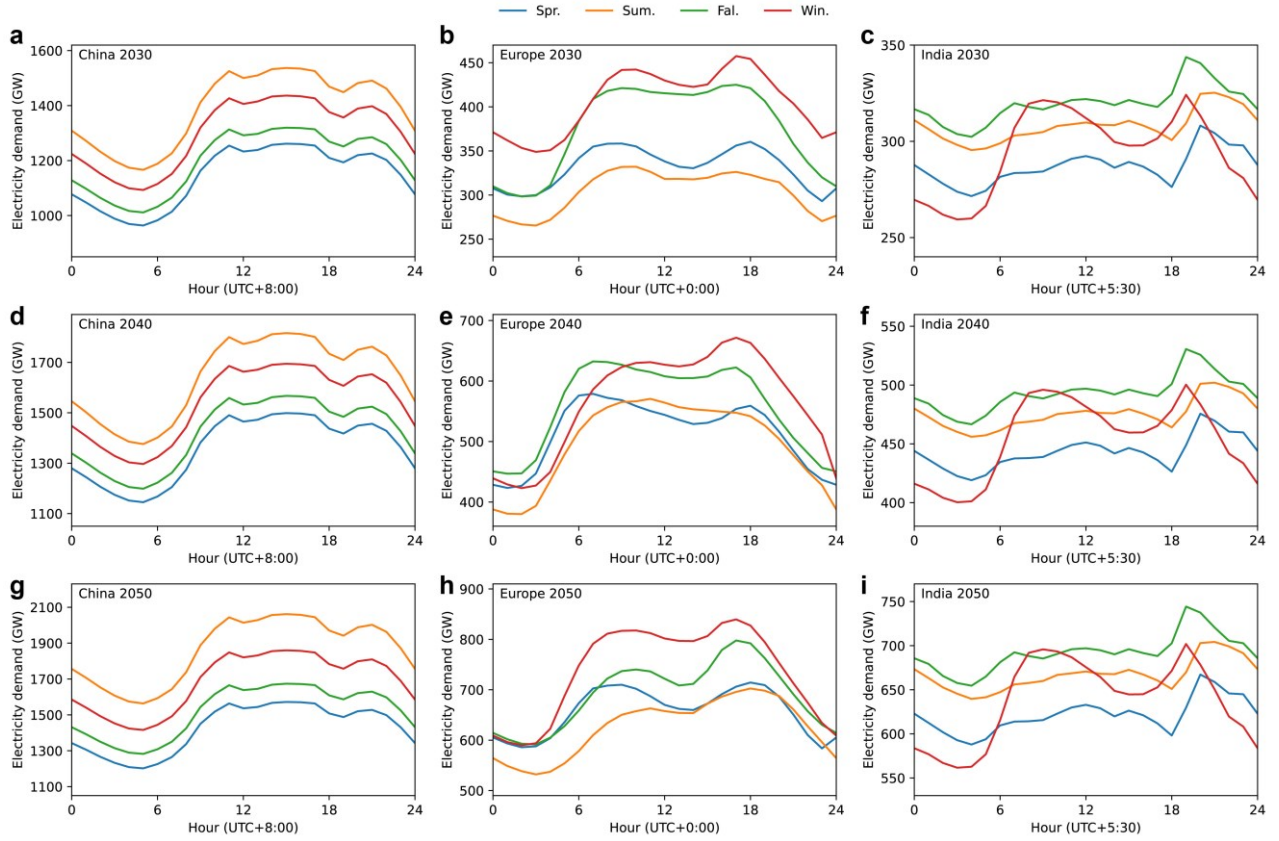
For each region and scenario, a paired comparison is used. The no-ERES baseline and the corresponding ERES cases share the same system configurations, including electricity demand, hourly load profile, renewable resource profile, technology cost trajectory, fuel cost, emission factor, transmission assumption and reserve requirement. The ERES cases introduce ERES as an additional storage-equivalent flexibility resource with explicit economic and technical parameters and are solved under different carbon price pathways.

Electricity system configuration

To comprehensively assess the value of ERES across different stages of energy decarbonization, we apply this modeling framework to China, Europe, and India—regions with distinct energy mixes, decarbonization roadmaps, and extensive electrified rail networks. Regional electricity demand projections for these regions are based on China Energy & Electricity Outlook 2022⁴⁶, the Ten-Year Network Development Plan (TYNDP) 2024 Scenarios Report⁴⁷ and World Energy Outlook 2024⁴⁸, as shown in Supplementary Fig. 4. To account for uncertainties in future energy system development, we adopt the mean values of generation projections across multiple scenarios outlined in these reports. To simulate the dynamics of electricity system operation, we set the load profile by linear scaling based on the current hourly demand profile from National Development and Reform Commission (NDRC) Typical Load Profiles of Provincial Grids⁴⁹, European Network of Transmission System Operators for Electricity (ENTSO-E) Power Statistics⁵⁰ and Power System Operation Corporation Ltd. (POSOCO) Electricity Demand Pattern Analysis⁵¹, as illustrated in Supplementary Fig. 5.



Supplementary Fig. 4 | Annual electricity demand projections of China, Europe and India in 2030 (a-c), 2040 (d-f) and 2050 (g-i). The geographical distribution of demand is allocated based on the current proportion of electricity load. Map data from © OpenStreetMap contributors, licensed under the Open Database License (ODbL)³³.



Supplementary Fig. 5 | Hourly power demand of China, Europe and India. a–c, China, Europe and India in 2030, respectively. d–f, Corresponding profiles in 2040. g–i, Corresponding profiles in 2050. Spr., Sum., Fal. and Win. denote spring, summer, fall and winter, respectively. UTC denotes Coordinated Universal Time.

The system value of ERES is quantified by its economic and environmental benefits, measured as reductions in total system cost and carbon emissions, respectively. Supplementary Tables 15–17 summarize the capital and O&M costs of thermal power plants in three regions. Technical parameters of these power plants, including energy efficiency and minimum power output, are also presented. The power generation emissions are calculated based on the CO₂ emission factors and the annual power generation of all thermal generators. Supplementary Tables 18–20 show the costs and CO₂ emission factors of fuels across the three regions. These costs are derived from IEA⁴⁸ and the emission factors are set according to ref.⁴⁴.

Supplementary Table 15. Costs and parameters of thermal power plants in China

Capital cost (USD kW⁻¹)	Operation and maintenance cost (USD kW⁻¹ yr⁻¹)	Efficiency (%)	Minimum power output (%)	Year
Subcritical Coal				
600	20	37	50	2025
600	20	37	50	2035
600	20	37	50	2045
Supercritical Coal				
700	30	41	50	2025
700	30	41	50	2035
700	30	41	50	2045
Ultra Supercritical Coal				
800	30	45	50	2025
800	30	46	50	2035
800	30	47	50	2045
Integrated Gasification Combined Cycle (IGCC)				
1100	49	45	50	2025
1050	44	47	50	2035
950	41	48	50	2045
Combined Cycle Gas Turbine (CCGT)				
560	20	57	40	2025
560	20	58	40	2035
560	20	59	40	2045
Gas turbine				
350	20	38	25	2025
350	20	40	25	2035
350	20	41	25	2045
Nuclear				
2800	170	33	100	2025
2725	170	33	100	2035
2575	170	33	100	2045

Supplementary Table 16. Costs and parameters of thermal power plants in Europe

Capital cost (USD kW⁻¹)	Operation and maintenance cost (USD kW⁻¹ yr⁻¹)	Efficiency (%)	Minimum power output (%)	Year
Subcritical Coal				
1700	45	39	50	2025
1700	45	39	50	2035
1700	45	39	50	2045
Supercritical Coal				
2000	60	43	50	2025
2000	60	43	50	2035
2000	60	43	50	2045
Ultra Supercritical Coal				
2200	65	46	50	2025
2200	65	47	50	2035
2200	65	48	50	2045
Integrated Gasification Combined Cycle (IGCC)				
2457	92	46	50	2025
2338	84	48	50	2035
2313	81	49	50	2045
Combined Cycle Gas Turbine (CCGT)				
1000	25	59	40	2025
1000	25	60	40	2035
1000	25	61	40	2045
Gas turbine				
500	20	40	25	2025
500	20	41	25	2035
500	20	42	25	2045
Nuclear				
6171	165	33	100	2025
4950	164	33	100	2035
4650	161	33	100	2045

Supplementary Table 17. Costs and parameters of thermal power plants in India

Capital cost (USD kW ⁻¹)	Operation and maintenance cost (USD kW ⁻¹ yr ⁻¹)	Efficiency (%)	Minimum power output (%)	Year
Subcritical Coal				
1000	35	36	50	2025
1000	35	36	50	2035
1000	35	36	50	2045
Supercritical Coal				
1200	50	40	50	2025
1200	50	40	50	2035
1200	50	40	50	2045
Ultra Supercritical Coal				
1400	55	41	50	2025
1400	55	42	50	2035
1400	55	43	50	2045
Integrated Gasification Combined Cycle (IGCC)				
1571	70	42	50	2025
1500	70	45	50	2035
1500	70	46	50	2045
Combined Cycle Gas Turbine (CCGT)				
700	25	56	40	2025
700	25	57	40	2035
700	25	58	40	2045
Gas turbine				
400	20	38	25	2025
400	20	40	25	2035
400	20	41	25	2045
Nuclear				
2800	140	33	100	2025
2800	140	33	100	2035
2800	140	33	100	2045

Supplementary Table 18. Costs and CO₂ emission factors of fuels in China

Average cost (USD MBtu ⁻¹)	CO ₂ emission factors (kg CO ₂ MBtu ⁻¹)	Year
Coal		
4.242	95.52	2025
3.696	95.52	2035
3.444	95.52	2045
Gas		
7.2	53.06	2025
8.2	53.06	2035
8.3	53.06	2045
Uranium		
0.98	0	2025
1.14	0	2035
1.3	0	2045

MBtu denotes million British thermal units.

Supplementary Table 19. Costs and CO₂ emission factors of fuels in Europe

Average cost (USD MBtu ⁻¹)	CO ₂ emission factors (kg CO ₂ MBtu ⁻¹)	Year
Coal		
2.856	95.52	2025
2.898	95.52	2035
2.688	95.52	2045
Gas		
6.5	53.06	2025
7.6	53.06	2035
7.7	53.06	2045
Uranium		
0.98	0	2025
1.14	0	2035
1.3	0	2045

MBtu denotes million British thermal units.

Supplementary Table 20. Costs and CO₂ emission factors of fuels in India

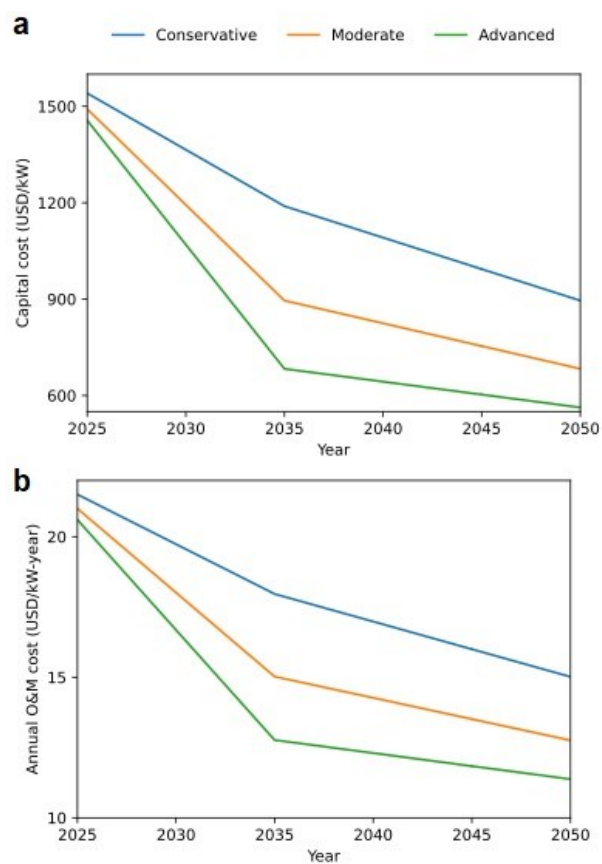
Average cost (USD MBtu ⁻¹)	CO ₂ emission factors (kg CO ₂ MBtu ⁻¹)	Year
Coal		
3.6	95.52	2025
3.14	95.52	2035
2.92	95.52	2045
Gas		
7.65	53.06	2025
8.71	53.06	2035
9.04	53.06	2045
Uranium		
0.98	0	2025
1.14	0	2035
1.3	0	2045

MBtu denotes million British thermal units.

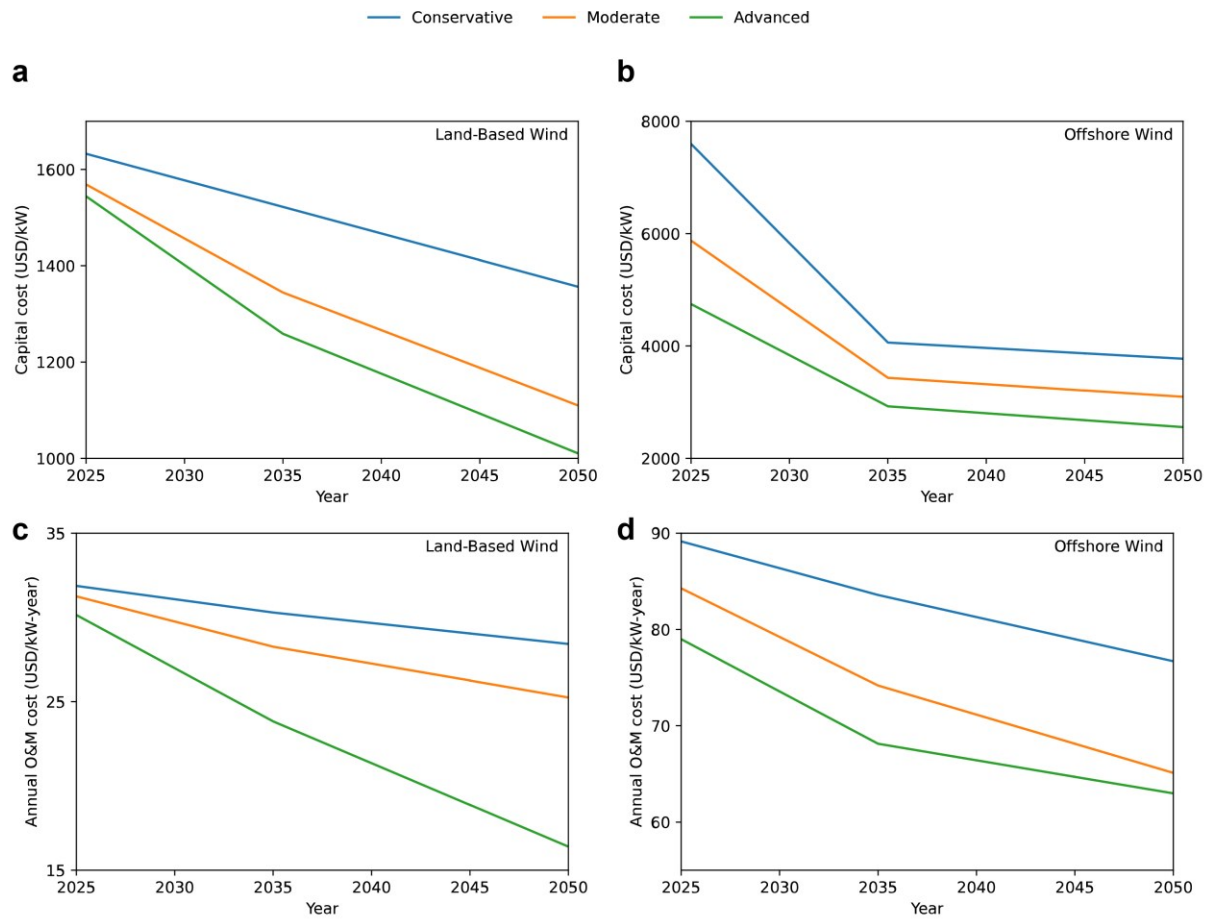
Renewable energy source technology innovation scenarios

The costs of renewable generation and storage, such as solar photovoltaics, wind, and batteries, have decreased substantially and are projected to continue to decline⁴⁵. Because uncertainty in these cost trajectories significantly influences the overall cost of carbon abatement in electricity systems, we examine how these cost trajectories affect decarbonization pathways and the systemic value of ERES. We explore three cost reduction scenarios based on the projections from the Department of Energy's national laboratories^{52,53}: conservative scenario: Historical investments come to market with continued industrial learning. Technology looks similar to today, with few changes from technology innovation. Public and private research and development (R&D) investment decreases; moderate scenario: Innovations observed in today's market become more widespread, and innovations nearly market-ready today come into the market. Current levels of public and private R&D investment continue. This scenario may be considered the expected level of technology innovation; advanced scenario: Innovations far from market-ready today are successful and become widespread in the market. New technology architectures could look different from those observed today. Public and private R&D investment increases.

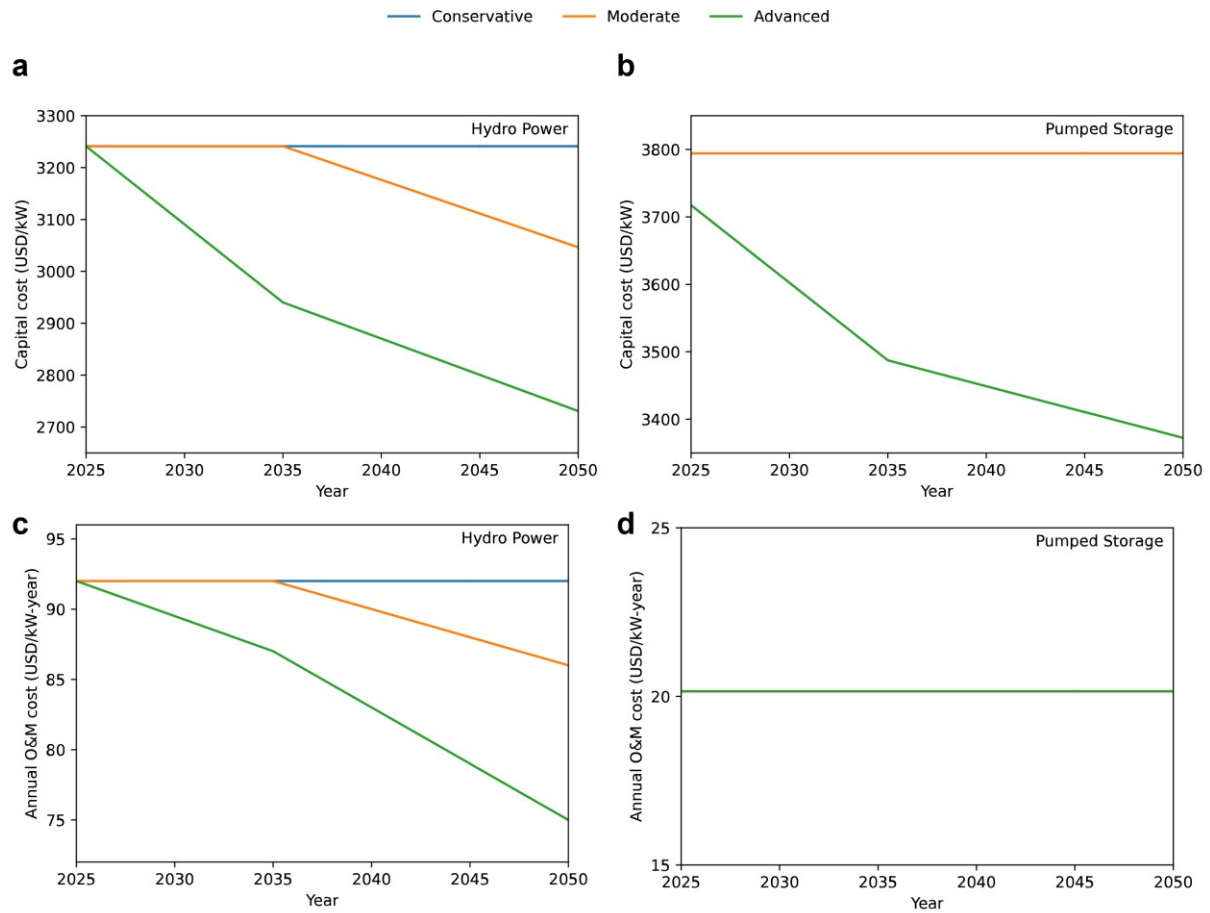
Four representative storage technologies are included in the model: 4-hour battery storage, 10-hour compressed-air energy storage, 15.5-hour pumped-hydro storage and 24-hour hydrogen-based storage. These technologies represent storage options with different duration, efficiency, cost and investment characteristics. Their inclusion allows the model to evaluate how ERES interacts with a heterogeneous mix of storage technologies.



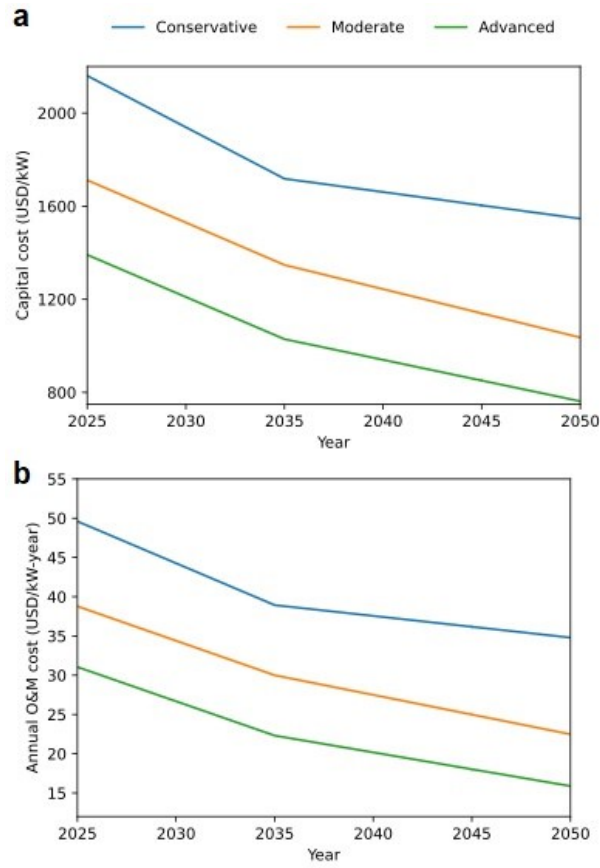
Supplementary Fig. 6 | Capital and O&M costs of solar PV in scenarios. a, Capital cost. **b,** Annual operation and maintenance cost. PV and O&M denote photovoltaic and operation and maintenance, respectively.



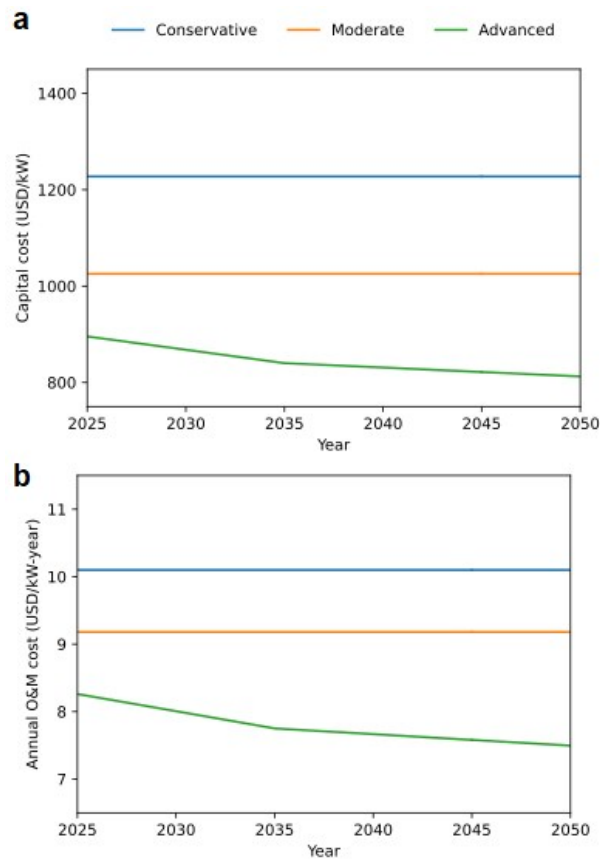
Supplementary Fig. 7 | Capital and O&M costs of wind in scenarios. a,b, Capital costs of land-based and offshore wind, respectively. **c,d,** Corresponding annual operation and maintenance costs. O&M denotes operation and maintenance.



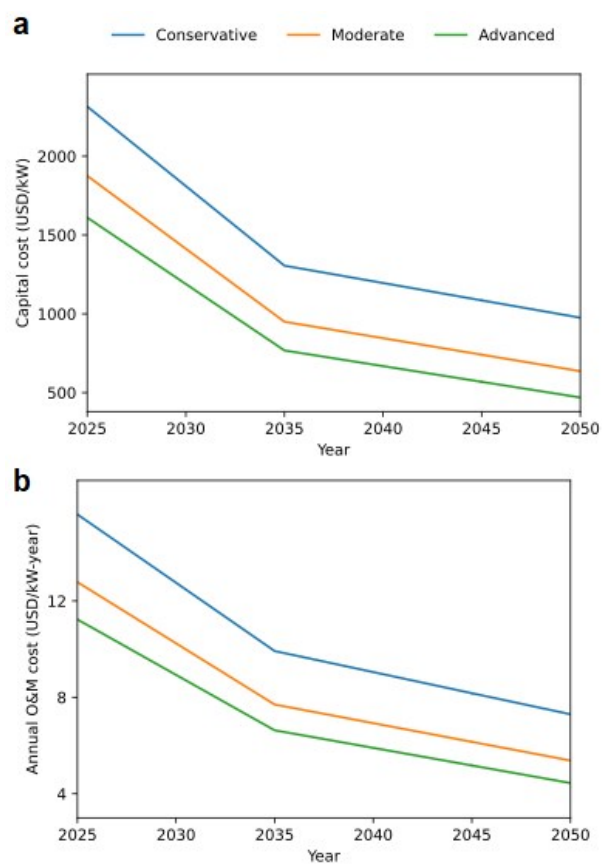
Supplementary Fig. 8 | Capital and O&M costs of hydropower and pumped storage in scenarios. a,b, Capital costs of hydropower and pumped storage, respectively. **c,d,** Corresponding annual operation and maintenance costs. O&M denotes operation and maintenance. Pumped storage facilities are assumed to have a round-trip efficiency of 74% and storage durations of 15.5 hours⁵⁴.



Supplementary Fig. 9 | Capital and O&M costs of battery storage in scenarios. a, Capital cost. **b,** Annual operation and maintenance cost. O&M denotes operation and maintenance. The battery storage systems are configured with a typical energy-to-power ratio of 4 hours and a round-trip efficiency of 85%⁵³.

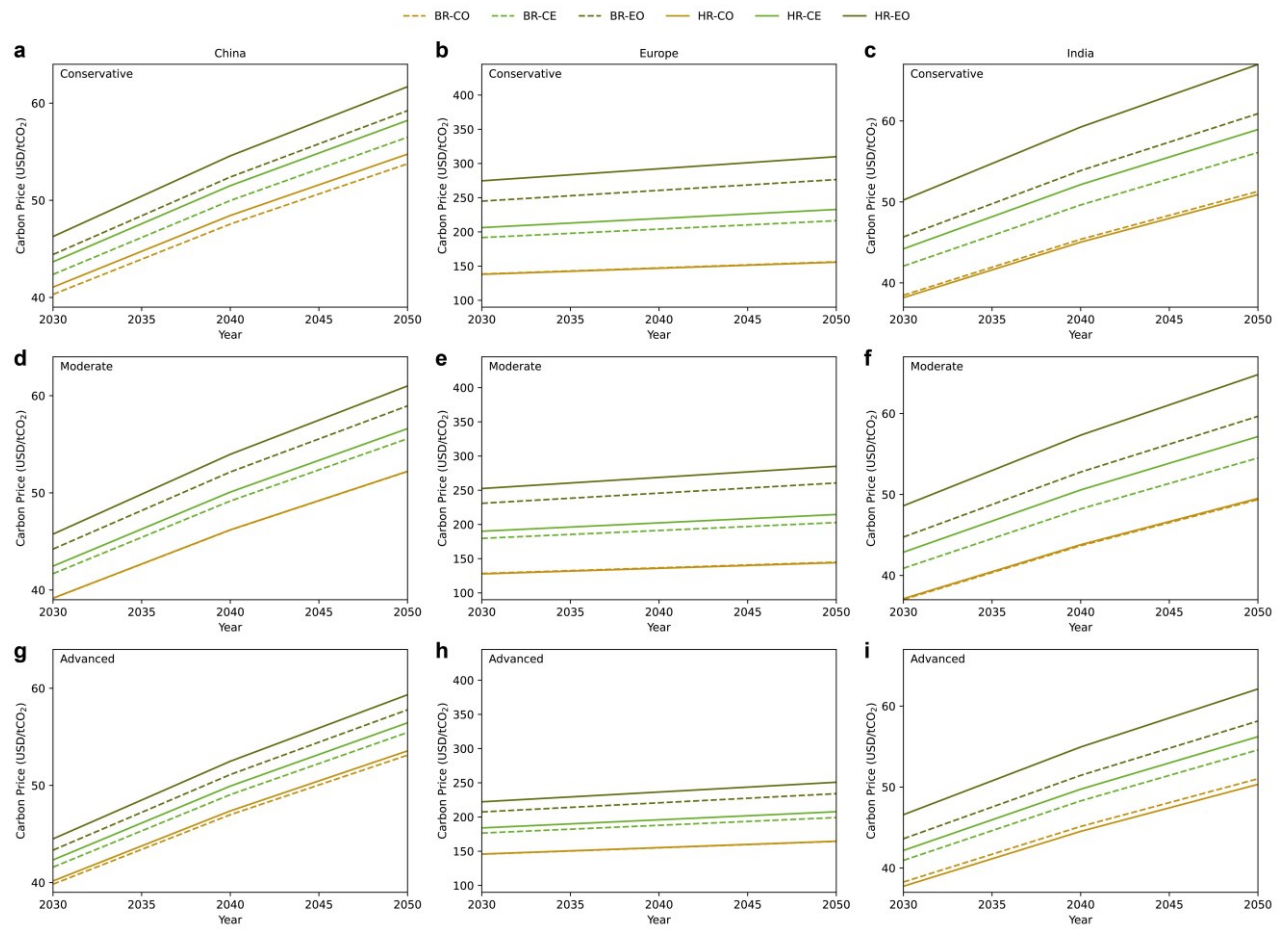


Supplementary Fig. 10 | Capital and O&M costs of compressed-air energy storage (CAES) in scenarios. a, Capital cost. **b,** Annual operation and maintenance cost. O&M denotes operation and maintenance. The CAES systems are assumed to have a round-trip efficiency of 59% and storage durations of 10 hours⁵².



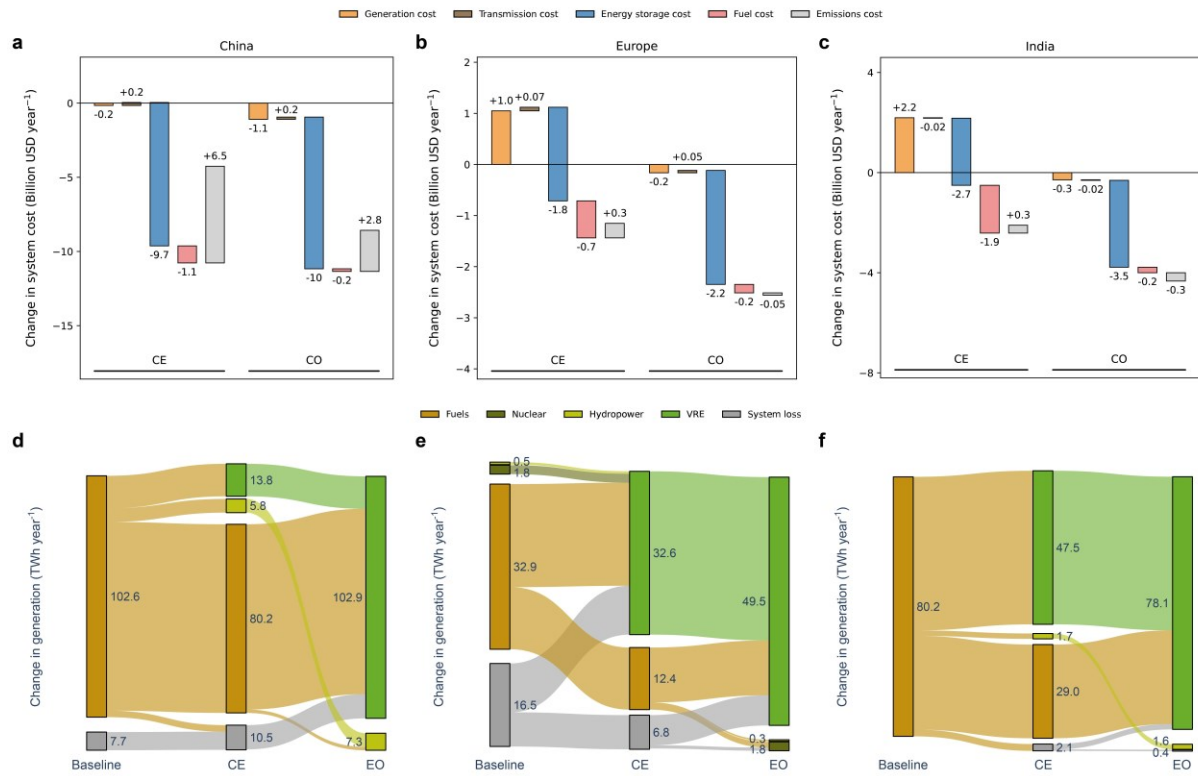
Supplementary Fig. 11 | Capital and O&M costs of hydrogen-based energy storage in scenarios. a, Capital cost. **b,** Annual operation and maintenance cost. O&M denotes operation and maintenance. The hydrogen-based energy storage systems are assumed to have a round-trip efficiency of 31% and storage durations of 24 hours⁵².

Carbon price pathways



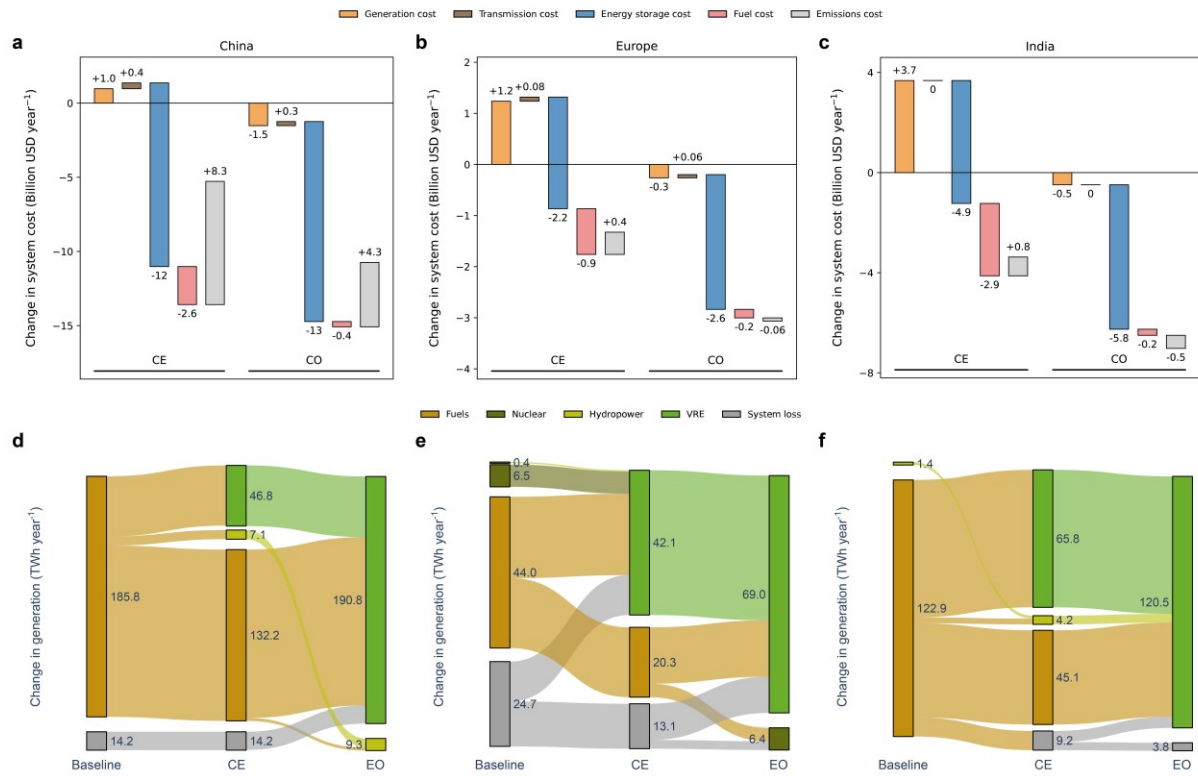
Supplementary Fig. 12 | CO, CE and EO pathways across scenarios. a–c, Conservative technology innovation scenarios for China, Europe and India, respectively. d–f, Corresponding moderate scenarios. g–i, Corresponding advanced scenarios. BR and HR denote base rail and high rail scenarios, respectively. CO, CE and EO denote cost-oriented, cost–emission balanced and emission-oriented pathway outcomes, respectively.

Supplementary outputs across scenarios



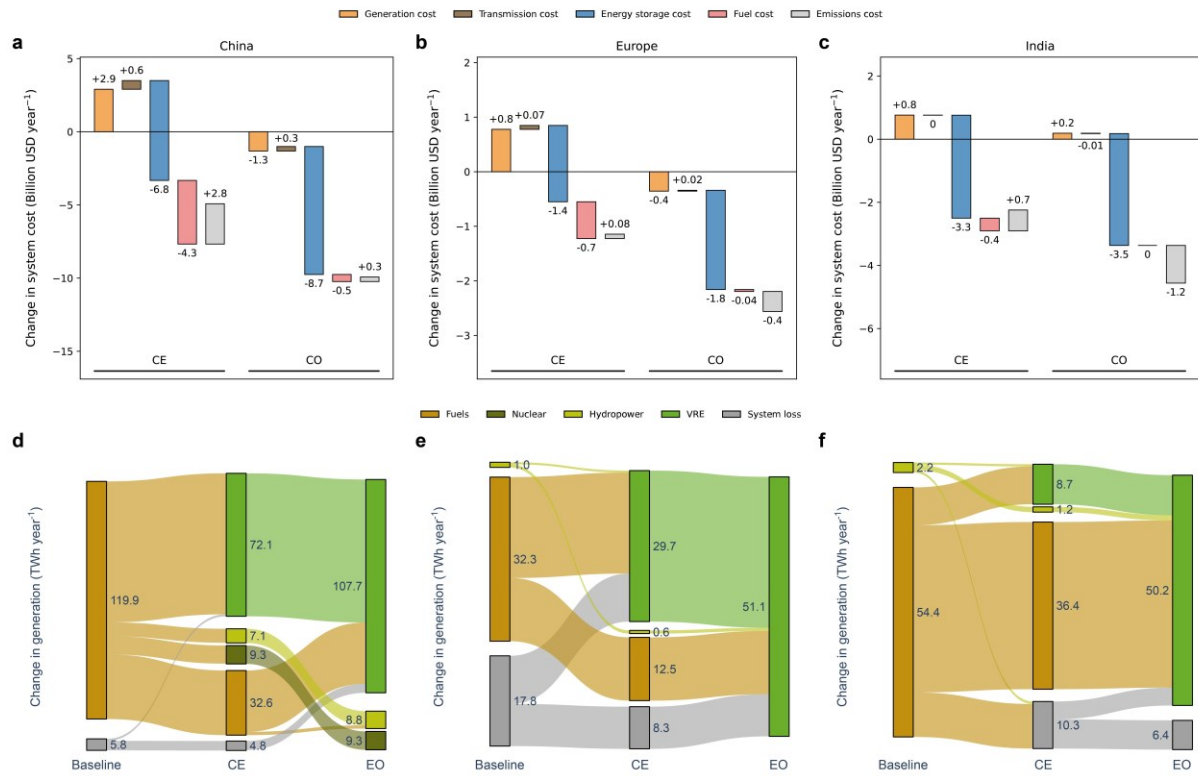
Supplementary Fig. 13 | System cost changes and generation-mix outcomes with Electrified Rail-Based Energy Storage in BR-C scenarios.

a–c, Decomposition of changes in total system cost under CE and CO pathways relative to the corresponding baseline. BR-C combines the base rail scenario with the conservative technology innovation trajectory. CE, CO and EO denote cost–emission balanced, cost-oriented and emission-oriented pathway outcomes, respectively. Negative values indicate cost reductions, whereas positive values indicate additional costs. **d–f**, Generation mixes in the baseline, CE and EO pathways. Fuels include coal-fired and gas-fired generation. The Sankey diagrams compare optimized annual generation by source among the independently solved baseline, CE and EO outcomes. Links visualize redistribution among generation categories and do not imply temporal transitions or physical energy flows between outcomes. VRE denotes variable renewable energy, including solar and wind power.



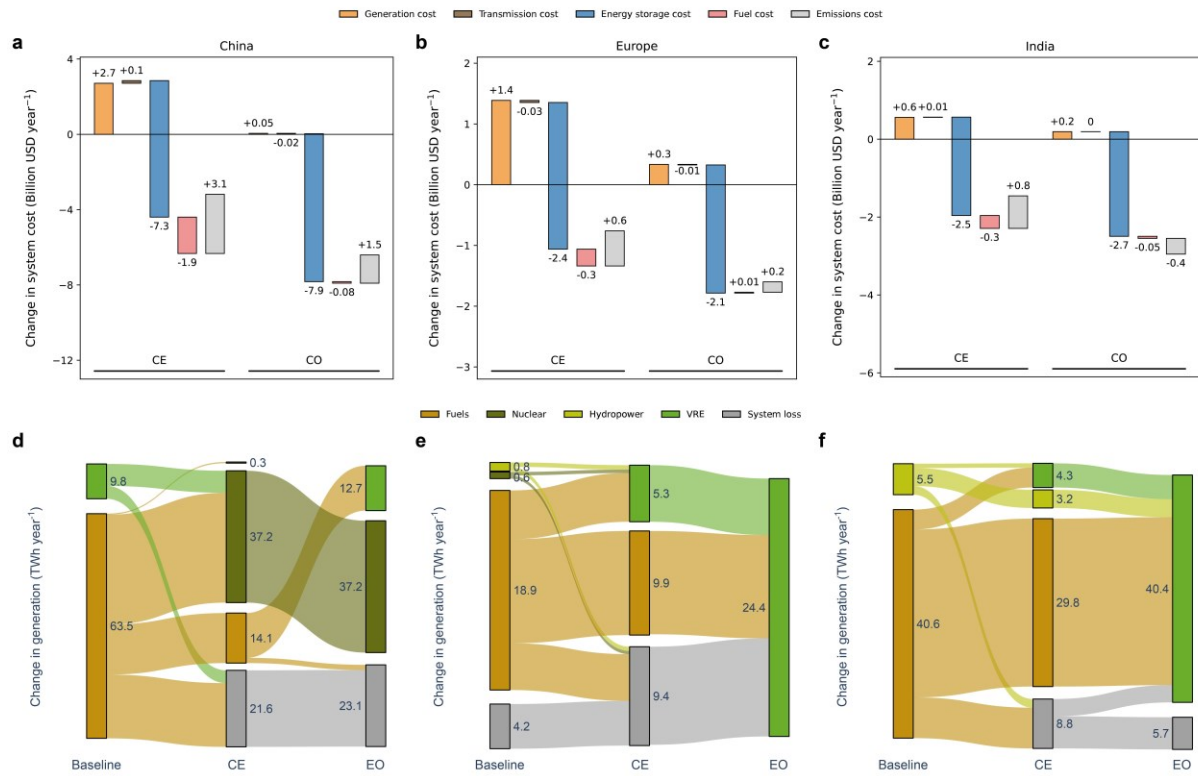
Supplementary Fig. 14 | System cost changes and generation-mix outcomes with Electrified Rail-Based Energy Storage in HR-C scenarios.

a–c, Decomposition of changes in total system cost under CE and CO pathways relative to the corresponding baseline. HR-C combines the high rail scenario with the conservative technology innovation trajectory. CE, CO and EO denote cost–emission balanced, cost-oriented and emission-oriented pathway outcomes, respectively. Negative values indicate cost reductions, whereas positive values indicate additional costs. **d–f**, Generation mixes in the baseline, CE and EO pathways. Fuels include coal-fired and gas-fired generation. The Sankey diagrams compare optimized annual generation by source among the independently solved baseline, CE and EO outcomes. Links visualize redistribution among generation categories and do not imply temporal transitions or physical energy flows between outcomes. VRE denotes variable renewable energy, including solar and wind power.



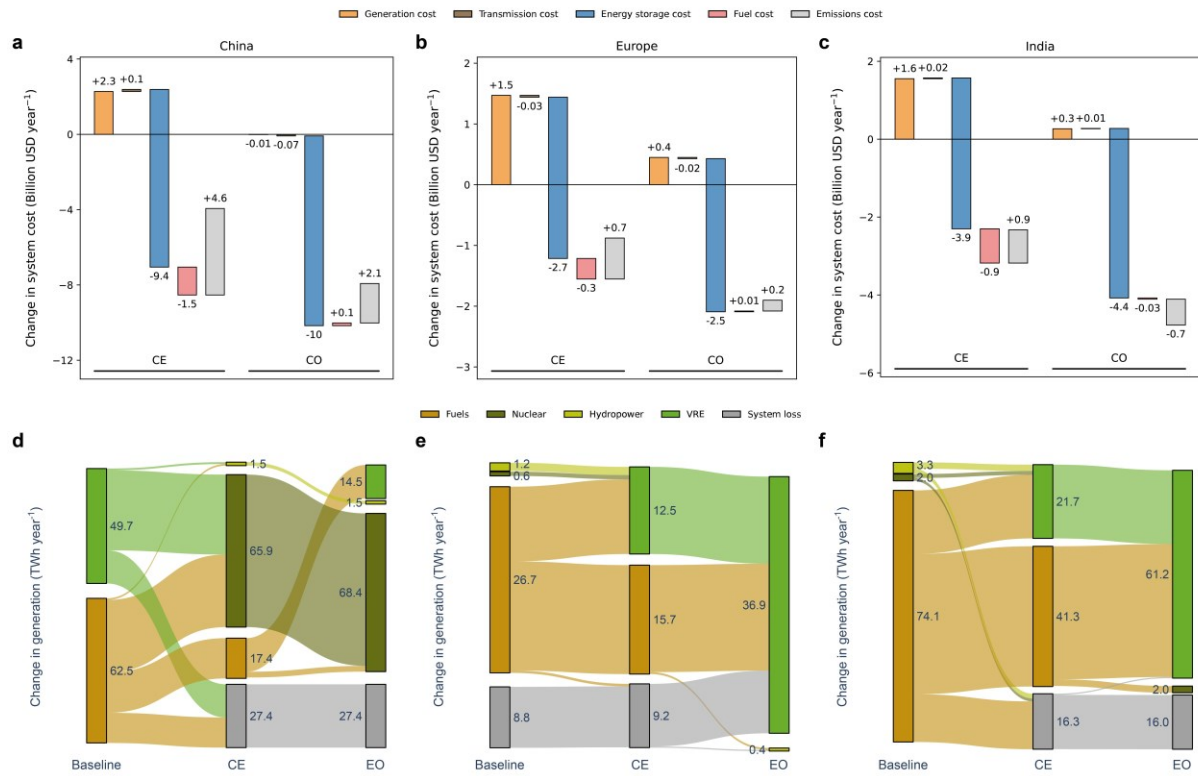
Supplementary Fig. 15 | System cost changes and generation-mix outcomes with Electrified Rail-Based Energy Storage in BR-M scenarios.

a–c, Decomposition of changes in total system cost under CE and CO pathways relative to the corresponding baseline. BR-M combines the base rail scenario with the moderate technology innovation trajectory. CE, CO and EO denote cost–emission balanced, cost-oriented and emission-oriented pathway outcomes, respectively. Negative values indicate cost reductions, whereas positive values indicate additional costs. **d–f**, Generation mixes in the baseline, CE and EO pathways. Fuels include coal-fired and gas-fired generation. The Sankey diagrams compare optimized annual generation by source among the independently solved baseline, CE and EO outcomes. Links visualize redistribution among generation categories and do not imply temporal transitions or physical energy flows between outcomes. VRE denotes variable renewable energy, including solar and wind power.



Supplementary Fig. 16 | System cost changes and generation-mix outcomes with Electrified Rail-Based Energy Storage in BR-A scenarios.

a–c, Decomposition of changes in total system cost under CE and CO pathways relative to the corresponding baseline. BR-A combines the base rail scenario with the advanced technology innovation trajectory. CE, CO and EO denote cost–emission balanced, cost-oriented and emission-oriented pathway outcomes, respectively. Negative values indicate cost reductions, whereas positive values indicate additional costs. **d–f**, Generation mixes in the baseline, CE and EO pathways. Fuels include coal-fired and gas-fired generation. The Sankey diagrams compare optimized annual generation by source among the independently solved baseline, CE and EO outcomes. Links visualize redistribution among generation categories and do not imply temporal transitions or physical energy flows between outcomes. VRE denotes variable renewable energy, including solar and wind power.



Supplementary Fig. 17 | System cost changes and generation-mix outcomes with Electrified Rail-Based Energy Storage in HR-A scenarios.

a–c, Decomposition of changes in total system cost under CE and CO pathways relative to the corresponding baseline. HR-A combines the high rail scenario with the advanced technology innovation trajectory. CE, CO and EO denote cost–emission balanced, cost-oriented and emission-oriented pathway outcomes, respectively. Negative values indicate cost reductions, whereas positive values indicate additional costs. **d–f**, Generation mixes in the baseline, CE and EO pathways. Fuels include coal-fired and gas-fired generation. The Sankey diagrams compare optimized annual generation by source among the independently solved baseline, CE and EO outcomes. Links visualize redistribution among generation categories and do not imply temporal transitions or physical energy flows between outcomes. VRE denotes variable renewable energy, including solar and wind power.

Sensitivity of system-level outcomes with respect to the auxiliary-load allocation parameter

To examine how auxiliary-load allocation affects the system-level value of ERES, we propagate the regional ERES capacity bounds corresponding to the lower, central and upper auxiliary-load cases defined in the Sensitivity of projected ERES capacities with respect to the auxiliary-load allocation parameter section through the capacity expansion models for China, Europe and India under the HR–M scenario. Each auxiliary-load case determines the corresponding regional ERES capacity bounds, while the electricity system configuration and all other ERES economic and technical parameters remain unchanged. For each region and auxiliary-load case, the CO and EO pathways follow the definitions in Table 2 and are obtained using the same interpolation convention described in Methods.

CO cost savings and EO operational CO₂ reductions are highest in the lower auxiliary-load case and lowest in the upper auxiliary-load case in all three regions (Supplementary Table 21). Across the three modeled regions, aggregate annual cost savings range from US\$20.0 billion to US\$23.1 billion under the CO pathway, while aggregate operational CO₂ reductions range from 202.5 to 218.3 Mt CO₂ yr⁻¹ under the EO pathway. Relative to the central case, the three-region aggregate CO cost savings increase by 3.1% in the lower auxiliary-load case and decrease by 11.1% in the upper auxiliary-load case; the corresponding EO operational CO₂ reduction increases by 1.0% and decreases by 6.4%, respectively. CO cost savings and EO operational CO₂ reductions remain positive in all nine paired cases.

Supplementary Table 21. Sensitivity of system-level outcomes with respect to the auxiliary-load allocation parameter under the HR–M scenario.

Region	Auxiliary-load case	CO cost saving (US\$ billion yr ⁻¹)	EO emission reduction (Mt CO ₂ yr ⁻¹)
China	Lower auxiliary-load case	13.33	116.98
China	Central case	12.92	115.96
China	Upper auxiliary-load case	11.39	107.64
Europe	Lower auxiliary-load case	3.16	13.8
Europe	Central case	2.99	12.72
Europe	Upper auxiliary-load case	2.77	11.69
India	Lower auxiliary-load case	6.65	87.52
India	Central case	6.55	87.52
India	Upper auxiliary-load case	5.81	83.14

HR–M combines the high rail scenario with the moderate technology innovation trajectory. CO and EO denote the cost-oriented and emission-oriented pathway outcomes, respectively.

Supplementary Method 4. ERES economic and technical parameterization

Cost boundary, currency conversion and inflation adjustment of ERES economic parameters

The economic parameterization of ERES includes only the incremental costs required for grid-interactive operation. It excludes the sunk costs of existing railway lines, trains and traction power infrastructure. The included components are: the capital expenditure (CAPEX) and fixed operation and maintenance (FOM) cost of the Train-to-Grid (T2G) coordination system; the additional CAPEX and FOM cost of retrofitting DC traction substations with reversible power flow capability; and the variable operation and maintenance (VOM) cost associated with regulation-induced train and track maintenance.

Throughout the ERES economic and technical parameterization section, source-reported values, official annual average exchange rates and U.S. Consumer Price Index for All Urban Consumers (CPI-U) values are retained at their published precision. Intermediate results are displayed to three significant figures to make the calculations traceable, while calculations and model inputs use unrounded values. The planning-level economic parameters reported in Table 1 are rounded to two significant figures to reflect the approximate nature of their analogy- and proxy-based derivation.

Because the cost dataset spans different currencies and price years, we normalize all monetary inputs to 2025 USD before integrating them into the capacity expansion model. For a cost reported in local currency in price year y , the normalized cost is calculated using supplementary equation (56).

$$C_{2025,USD} = C_{y,local} \times FX_y^{USD/local} \times \frac{CPI_{2025}^{US}}{CPI_y^{US}} \quad (56)$$

where $C_{y,local}$ is the source cost in its original currency and price year; $FX_y^{USD/local}$ is the annual average exchange rate in year y , expressed in US dollars per unit of the source currency; and CPI_{2025}^{US} and CPI_y^{US} are the annual-average US Consumer Price Index values for the source and target years, respectively. Costs originally reported in US dollars do not require currency conversion and are adjusted only by the CPI ratio.

For euro-denominated inputs, we use annual-average exchange rates from the European Central Bank (ECB)⁵⁵. The rates are 1.329 USD per EUR for 2014 and 1.130 USD per EUR for 2017. For pound-sterling- and Swedish-krona-denominated maintenance inputs, annual-average USD-per-local-currency rates are obtained by cross-conversion of the ECB annual series `EXR.A.USD.EUR.SP00.A`, `EXR.A.GBP.EUR.SP00.A` and `EXR.A.SEK.EUR.SP00.A`⁵⁵. The resulting rates used in Supplementary Tables 24 and 25 are 1.6040 USD per GBP for 2011 and 0.1477, 0.1461 and 0.1170 USD per SEK for 2012, 2014 and 2016, respectively. Inflation adjustment uses the US Consumer Price Index for All Urban Consumers (CPI-U)⁵⁶. The annual-average CPI-U values are 232.957 for 2013, 236.736 for 2014, 245.120 for 2017 and 321.943 for 2025. Annual averages are used consistently for both the source and target years.

Train-to-Grid coordination system cost

The T2G coordination system represents communication, metering, control and dispatch functions that allow railway flexibility to be coordinated with electricity system operation. This coordination layer is required for both AC and DC ERES. We estimate its CAPEX and FOM costs using published cost structures for virtual power plant (VPP) applications with corresponding aggregation, communication, control and grid-coordination functions.

Three VPP cost structures reported by Gutschi et al.⁵⁷ are used: Case 1a, a market-driven VPP for flexibility provision; Case 1b, a market-driven VPP operating under distribution system constraints; and Case 2, a VPP used to manage grid access in a constrained network. The fixed and variable CAPEX and operating expenditure (OPEX) components are summarized in Supplementary Table 22.

Supplementary Table 22. VPP cost components used to derive the T2G coordination system cost.

Case	Fixed CAPEX (EUR per VPP system)	Variable CAPEX (EUR MW ⁻¹)	Fixed OPEX (EUR yr ⁻¹ per VPP system)	Variable OPEX (EUR client ⁻¹ yr ⁻¹)
1a	50,000	3,000	65,240	3,860
1b	70,000	3,000	66,440	3,860
2	50,000	4,000	14,000	900

VPP, T2G, CAPEX and OPEX denote virtual power plant, Train-to-Grid, capital expenditure and operating expenditure, respectively.

To convert the reported per-system, per-MW and per-client VPP cost components into capacity-normalized model inputs, the fixed system-level costs are allocated over the coordination capacity P_{sys} , and the client-level recurring costs are converted using the flexible capacity per client P_{client} . The reference calculation uses $P_{\text{sys}} = 100$ MW and $P_{\text{client}} = 1$ MW per client⁵⁷. For each VPP case $c \in \{1a, 1b, 2\}$, let $c_{c,2017}^{\text{CAPEX}}$ and $c_{c,2017}^{\text{FOM}}$ denote the resulting capacity-normalized CAPEX and annual FOM in 2017 euros, expressed in EUR kW⁻¹ and EUR kW⁻¹ yr⁻¹, respectively.

$$c_{c,2017}^{\text{CAPEX}} = \frac{C_c^{\text{CAPEX,F}}}{1,000P_{\text{sys}}} + \frac{C_c^{\text{CAPEX,V}}}{1,000} \quad (57)$$

$$c_{c,2017}^{\text{FOM}} = \frac{C_c^{\text{OPEX,F}}}{1,000P_{\text{sys}}} + \frac{C_c^{\text{OPEX,V}}}{1,000P_{\text{client}}} \quad (58)$$

where $C_c^{\text{CAPEX,F}}$ and $C_c^{\text{OPEX,F}}$ are the fixed CAPEX and fixed annual OPEX per VPP system, respectively; $C_c^{\text{CAPEX,V}}$ is the variable CAPEX per MW of connected flexible capacity; and $C_c^{\text{OPEX,V}}$ is the variable annual OPEX per client. The factor 1,000 converts MW to kW. The client-dependent OPEX is mapped to FOM because it is an annually recurring platform and communication cost allocated to managed capacity. The allocation gives CAPEX values of 3.5, 3.7 and 4.5 EUR kW⁻¹, and FOM values of 4.5, 4.5 and 1.0 EUR kW⁻¹ yr⁻¹, for Cases 1a, 1b and 2, respectively. We then apply the common conversion procedure in the Cost boundary, currency conversion and inflation adjustment of ERES economic parameters section using the 2017 annual-average exchange rate and CPI-U values. The corresponding estimates in 2025 USD are summarized in Supplementary Table 23.

Supplementary Table 23. T2G coordination system costs for the considered cases.

Case	CAPEX (2025 USD kW⁻¹)	FOM (2025 USD kW⁻¹ yr⁻¹)
1a	5.2	6.7
1b	5.5	6.7
2	6.7	1.5

T2G, CAPEX and FOM denote Train-to-Grid, capital expenditure and fixed operation and maintenance, respectively.

Because the ERES coordination layer combines aggregation, communication, control, dispatch-interface, and grid-coordination functions, no single VPP case includes the same combination of functions. We therefore use the average CAPEX values and the average FOM values from Cases 1a, 1b and 2 as the T2G coordination-system inputs in Table 1 and in the regional and global estimates reported in the main text. The resulting inputs are 5.8 USD kW⁻¹ for CAPEX and 5.0 USD kW⁻¹ yr⁻¹ for FOM.

DC reversible substation retrofit cost

Existing DC traction substations commonly use diode rectifiers that transmit power from the upstream AC grid to the traction network but do not permit reverse power export⁵⁸. We therefore assign an additional reversible substation retrofit cost to the DC share of ERES capacity. This cost covers the power conversion equipment and its engineering and system integration.

Based on the analysis of recuperating traction-substation configurations, the thyristor line-commutated inverter (TCI) is selected for two reasons: it enables reverse power export while retaining the existing rectifier transformer and diode rectifier, and it has the lowest reported equipment cost among the compared configurations⁵⁹. The reported TCI has a rated reverse power capacity of 3 MW and an estimated equipment cost of USD 0.22 million. Its unit equipment cost in 2013 is given in supplementary equation (59).

$$C_{TCI,2013}^{\text{equipment}} = \frac{0.22 \times 10^6 \text{USD}}{3 \times 10^3 \text{kW}} = 73.3 \text{ USD kW}^{-1} \quad (59)$$

The source study estimates that engineering and integration costs account for 50–100% of the TCI equipment price⁵⁹. We use the midpoint of the reported range, $m_{EI} = 75\%$, for the DC reversible-substation retrofit cost input used in Table 1 and in the regional and global estimates reported in the main text. The resulting DC reversible-substation retrofit CAPEX in 2013 is calculated using supplementary equation (60).

$$C_{DC,\text{retrofit},2013}^{\text{CAPEX}} = C_{TCI,2013}^{\text{equipment}} (1 + m_{EI}) = 128 \text{ USD kW}^{-1} \quad (60)$$

The installed retrofit CAPEX is then adjusted to 2025 USD using supplementary equation (61).

$$C_{DC,\text{retrofit},2025}^{\text{CAPEX}} = C_{DC,\text{retrofit},2013}^{\text{CAPEX}} \frac{321.943}{232.957} = 177 \text{ USD kW}^{-1} \quad (61)$$

In the absence of a railway-specific FOM estimate for reversible substation retrofits, we adopt a simplified ratio of 1.5% of installed capital cost per year based on a general estimate for electrical-equipment maintenance costs⁶⁰.

$$C_{DC,\text{retrofit},2025}^{\text{FOM}} = 0.015 C_{DC,\text{retrofit},2025}^{\text{CAPEX}} = 2.66 \text{ USD kW}^{-1} \text{ yr}^{-1} \quad (62)$$

The total CAPEX and FOM of AC and DC ERES are specified separately in supplementary equations (63)–(66).

$$C_{AC}^{\text{CAPEX}} = C_{T2G,2025}^{\text{CAPEX}} \approx 5.8 \text{ USD kW}^{-1} \quad (63)$$

$$C_{DC}^{\text{CAPEX}} = C_{T2G,2025}^{\text{CAPEX}} + C_{DC,\text{retrofit},2025}^{\text{CAPEX}} \approx 180 \text{ USD kW}^{-1} \quad (64)$$

$$C_{AC}^{\text{FOM}} = C_{T2G,2025}^{\text{FOM}} \approx 5.0 \text{ USD kW}^{-1} \text{ yr}^{-1} \quad (65)$$

$$C_{DC}^{\text{FOM}} = C_{T2G,2025}^{\text{FOM}} + C_{DC,\text{retrofit},2025}^{\text{FOM}} \approx 7.7 \text{ USD kW}^{-1} \text{ yr}^{-1} \quad (66)$$

For the mixed AC/DC European railway network in 2025, AC and DC ERES are represented as separate projects. The AC and DC shares derived from official ERA electrification system statistics are 62.65% and 37.35%, respectively²⁹. The electrified mainline railways considered in China and India are represented as AC systems and are not assigned the DC reversible-substation retrofit cost. For future railway expansion, newly built DC mainline railways are assumed to be equipped with traction supply interfaces capable of bidirectional power exchange at the design stage. Therefore, no additional reversible substation retrofit cost is assigned to the newly built railway share.

ERES variable operation and maintenance cost

The variable operation and maintenance cost is used to represent the marginal railway maintenance cost caused by ERES regulation. Existing railway operation and maintenance cost models are usually specified on a distance or time basis, such as maintenance cost per train kilometer, maintenance cost per locomotive kilometer, or scheduled inspection and overhaul cycles^{61,62}. These formulations are suitable for conventional railway operation, but they do not directly capture the incremental cost of ERES regulation because ERES changes the traction and braking power profile without changing the physical distance traveled or the scheduled operating time of trains. We therefore estimate the ERES VOM cost as a marginal cost per MWh of ERES electricity discharged.

The ERES maintenance cost is decomposed into train-related and track-related components in supplementary equation (67).

$$C_{\text{ERES}}^{\text{VOM}} = C_{\text{ERES}}^{\text{train}} + C_{\text{ERES}}^{\text{track}} \quad (67)$$

where $C_{\text{ERES}}^{\text{VOM}}$ is the VOM cost used in the capacity expansion model; $C_{\text{ERES}}^{\text{train}}$ is the marginal train maintenance cost and $C_{\text{ERES}}^{\text{track}}$ is the marginal track maintenance cost. The train component is further decomposed into the cost associated with electric motors and power electronics, and the cost associated with mechanical transmission, suspension and wheel equipment, as specified in supplementary equation (68).

$$C_{\text{ERES}}^{\text{train}} = C_{\text{ERES}}^{\text{EM}} + C_{\text{ERES}}^{\text{TSW}} \quad (68)$$

where $C_{\text{ERES}}^{\text{EM}}$ denotes the marginal cost for electric motors and power electronics, and $C_{\text{ERES}}^{\text{TSW}}$ denotes the marginal cost for transmission, suspension and wheel equipment.

Direct field measurements of marginal maintenance cost under ERES operation are not yet available. We therefore use a proxy-based approach. Because ERES stores energy through mechanical motion and repeated electromechanical conversion, the VOM cost of flywheel energy storage (FES) is used as the proxy for the electric motor and power electronics component. The reported FES VOM is 2.0 EUR MWh⁻¹ on a 2014 cost basis⁶³. Using the 2014 annual-average exchange rate of 1.329 USD per EUR and the CPI-U values given in the Cost boundary, currency conversion and inflation adjustment of ERES economic parameters section, this value is converted to 2025 USD using supplementary equation (69).

$$C_{\text{FES},2025}^{\text{VOM}} = 2.0 \times 1.329 \times \frac{321.943}{236.736} = 3.62 \text{ USD MWh}^{-1} \quad (69)$$

To account for the more complex operating environment of onboard traction equipment, including vibration and temperature variation, the factor $k_{\text{env}} = 1.2$ is applied in supplementary equation (70).

$$C_{\text{ERES}}^{\text{EM}} = k_{\text{env}} C_{\text{FES},2025}^{\text{VOM}} = 4.34 \text{ USD MWh}^{-1} \quad (70)$$

The marginal cost for transmission, suspension and wheel equipment is estimated using the relative maintenance cost structure of traction-related and mechanical equipment. Because public data on component-level train maintenance cost shares are limited, we follow the approach used in locomotive total cost of ownership studies, where component cost ratios are approximated using vehicle maintenance cost decomposition data⁶⁴. The ratio between the mechanical equipment component and the electric motor and power electronics component $k_{\text{mech/elec}}$ is set to 0.65.

$$C_{\text{ERES}}^{\text{TSW}} = k_{\text{mech/elec}} C_{\text{ERES}}^{\text{EM}} = 2.82 \text{ USD MWh}^{-1} \quad (71)$$

The resulting train-related marginal maintenance cost is calculated using supplementary equation (72).

$$C_{\text{ERES}}^{\text{train}} = 4.34 + 2.82 = 7.16 \text{ USD MWh}^{-1} \quad (72)$$

The track-related cost accounts for additional wheel–rail interaction associated with ERES regulation. Track damage depends on axle load, wheel–rail contact, dissipated energy and other nonlinear mechanisms⁶⁵. To obtain a planning-level estimate, we use the observed ratio between track and train marginal maintenance costs in railway operation. Each maintenance-cost observation is converted separately to 2025 USD, as summarized in Supplementary Tables 24 and 25.

Supplementary Table 24. Train marginal maintenance cost in 2025 USD.

Case	Cost (local currency train-km⁻¹)	Price year	Exchange rate (USD per local-currency unit)	CPI-U	Normalized cost (2025 USD train-km⁻¹)
1 ⁶⁶	1.555 GBP	2011	1.6040	224.939	3.570
2 ⁶⁶	1.820 GBP	2011	1.6040	224.939	4.178
3 ⁶⁶	1.330 GBP	2011	1.6040	224.939	3.053
4 ⁶⁶	1.170 GBP	2011	1.6040	224.939	2.686
5 ⁶⁶	0.905 GBP	2011	1.6040	224.939	2.078
6 ⁶⁶	0.780 GBP	2011	1.6040	224.939	1.791
7 ⁶⁶	2.140 GBP	2011	1.6040	224.939	4.913
8 ⁶⁶	1.965 GBP	2011	1.6040	224.939	4.511
9 ⁶⁶	0.995 GBP	2011	1.6040	224.939	2.284
10 ⁶⁶	0.925 GBP	2011	1.6040	224.939	2.124
11 ⁶⁶	1.580 GBP	2011	1.6040	224.939	3.627
12 ⁶⁶	1.475 GBP	2011	1.6040	224.939	3.386
13 ⁶⁶	1.230 GBP	2011	1.6040	224.939	2.824
14 ⁶¹	1.037 USD	2023	1.0000	304.702	1.096
15 ⁶⁷	1.625 EUR	2024	1.0824	313.689	1.805

CPI-U denotes the U.S. Consumer Price Index for All Urban Consumers.

Supplementary Table 25. Track marginal maintenance cost in 2025 USD.

Case	Cost (local currency tonne-km ⁻¹)	Price year	Exchange rate (USD per local-currency unit)	CPI-U	Normalized cost (2025 USD tonne-km ⁻¹)
1 ⁶⁸	0.00032 EUR	1998	1.1226	163	0.00071
2 ⁶⁹	0.00139 EUR	1999	1.066	166.6	0.002863
3 ⁶⁸	0.00014 EUR	2000	0.9241	172.2	0.000242
4 ⁶⁸	0.00013 EUR	2001	0.896	177.1	0.000212
5 ⁶⁸	0.00024 EUR	2001	0.896	177.1	0.000391
6 ⁶⁸	0.00055 EUR	2001	0.896	177.1	0.000896
7 ⁷⁰	0.00142 EUR	2006	1.2564	201.6	0.002849
8 ⁷⁰	0.00156 EUR	2006	1.2564	201.6	0.00313
9 ⁷⁰	0.00122 EUR	2006	1.2564	201.6	0.002448
10 ⁷⁰	0.00107 EUR	2006	1.2564	201.6	0.002147
11 ⁷⁰	0.00125 EUR	2006	1.2564	201.6	0.002508
12 ⁷⁰	0.00097 EUR	2006	1.2564	201.6	0.001946
13 ⁷⁰	0.00159 EUR	2006	1.2564	201.6	0.00319
14 ⁷⁰	0.00178 EUR	2006	1.2564	201.6	0.003571
15 ⁷¹	0.0058 SEK	2012	0.1477	229.594	0.001201
16 ⁷¹	0.0053 SEK	2012	0.1477	229.594	0.001098
17 ⁷¹	0.0078 SEK	2012	0.1477	229.594	0.001615
18 ⁷¹	0.0094 SEK	2012	0.1477	229.594	0.001947
19 ⁷²	0.0065 SEK	2014	0.1461	236.736	0.001291
20 ⁷²	0.0094 SEK	2014	0.1461	236.736	0.001868
21 ⁷²	0.0120 SEK	2014	0.1461	236.736	0.002384
22 ⁷²	0.0084 SEK	2016	0.117	240.007	0.001318

CPI-U denotes the U.S. Consumer Price Index for All Urban Consumers.

Let $c_{i,\text{train}}$ denote the i th normalized train-maintenance observation in Supplementary Table 24, expressed in 2025 USD train-km⁻¹, and let $c_{i,\text{track}}$ denote the i th normalized track-maintenance observation in Supplementary Table 25, expressed in 2025 USD tonne-km⁻¹. The average train-maintenance and track-maintenance costs are calculated using supplementary equations (73) and (74).

$$\bar{c}_{\text{train}} = \frac{1}{15} \sum_{i=1}^{15} c_{i,\text{train}} = 2.93 \text{ USD train-km}^{-1} \quad (73)$$

$$\bar{c}_{\text{track}} = \frac{1}{22} \sum_{i=1}^{22} c_{i,\text{track}} = 0.00181 \text{ USD tonne-km}^{-1} \quad (74)$$

Using representative train masses M_j of 750 tonnes for passenger trains and 1,750 tonnes for freight trains, the track-to-train marginal maintenance ratio ρ^j is calculated using supplementary equation (75).

$$\rho^j = \frac{\bar{c}_{\text{track}} M_j}{\bar{c}_{\text{train}}}, j \in \{P, F\} \quad (75)$$

Applying $\rho^P = 0.463$ and $\rho^F = 1.08$ to the ERES train maintenance cost gives the track-related marginal maintenance costs in supplementary equations (76) and (77).

$$C_{\text{ERES}}^{\text{track},P} = \rho^P C_{\text{ERES}}^{\text{train}} = 0.463 \times 7.16 = 3.32 \text{ USD MWh}^{-1} \quad (76)$$

$$C_{\text{ERES}}^{\text{track},F} = \rho^F C_{\text{ERES}}^{\text{train}} = 1.08 \times 7.16 = 7.73 \text{ USD MWh}^{-1} \quad (77)$$

The total VOM cost is therefore calculated using supplementary equations (78) and (79).

$$C_{\text{ERES}}^{\text{VOM},P} = C_{\text{ERES}}^{\text{train}} + C_{\text{ERES}}^{\text{track},P} = 10.5 \text{ USD MWh}^{-1} \quad (78)$$

$$C_{\text{ERES}}^{\text{VOM},F} = C_{\text{ERES}}^{\text{train}} + C_{\text{ERES}}^{\text{track},F} = 14.9 \text{ USD MWh}^{-1} \quad (79)$$

Because the railway electricity-consumption data indicate passenger and freight energy shares of approximately 44.5% and 55.5%, respectively, the global energy-weighted VOM is obtained using supplementary equation (80).

$$C_{\text{ERES}}^{\text{VOM}} = 44.5\% \times C_{\text{ERES}}^{\text{VOM},P} + 55.5\% \times C_{\text{ERES}}^{\text{VOM},F} \approx 13 \text{ USD MWh}^{-1} \quad (80)$$

Design of the cost sensitivity analysis

The T2G coordination system cost, DC reversible substation retrofit cost and ERES VOM are planning-level estimates derived from analogy- or proxy-based evidence. We conduct sensitivity tests to quantify how each cost group affects average annual total system cost savings, annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction.

For each T2G coordination-system or ERES VOM setting, the sensitivity analysis covers 18 combinations formed by three regions (China, Europe and India), two railway development scenarios (BR and HR) and three technology innovation scenarios (C, M and A). For each DC reversible-substation retrofit setting, the analysis covers the six European combinations formed by BR or HR and C, M or A. Each perturbation case is compared with the ERES case for the same region and scenario using the cost inputs in Table 1 and Supplementary Table 26. Only one cost group is changed in each run. T2G CAPEX and FOM are varied jointly because both values are recalculated from the same VPP cost components; DC retrofit CAPEX and FOM are varied jointly because both values are calculated from the same percentage of the TCI equipment price. The CE carbon price pathway, ERES capacity bounds, temporal availability, round-trip efficiency, depth of discharge and all inputs outside the tested cost group are held fixed. Each perturbation case is independently reoptimized in SWITCH.

Supplementary Table 26 reports the cost inputs used for comparison and the tested inputs for the three cost groups. For the T2G coordination system, the comparison inputs are CAPEX of 5.8 USD kW⁻¹ and FOM of 5.0 USD kW⁻¹ yr⁻¹, calculated using a coordination capacity allocation of 100 MW; the tested settings are CAPEX of 6.6 USD kW⁻¹ and FOM of 5.7 USD kW⁻¹ yr⁻¹ using 50 MW, and CAPEX of 13 USD kW⁻¹ and FOM of 11 USD kW⁻¹ yr⁻¹ using 10 MW. All three settings use the fixed and capacity-dependent VPP cost components reported in the source study. For the DC reversible substation retrofit, the comparison input assumes that engineering and integration costs account for 75% of the TCI equipment price, whereas the tested bounds are 50% and 100%. For ERES VOM, the comparison input is 13 USD MWh⁻¹ and the tested inputs are 6.5 USD MWh⁻¹, 26 USD MWh⁻¹ and 65 USD MWh⁻¹. The DC retrofit tests apply only to Europe because the modeled mainline railways in China and India use AC traction systems.

Supplementary Table 26. Design of sensitivity tests for Electrified Rail-Based Energy Storage (ERES) economic cost assumptions.

Cost group	Cost input used for comparison	Tested inputs	Basis of tested inputs
T2G coordination system	CAPEX = 5.8; FOM = 5.0	1. CAPEX = 6.6; FOM = 5.7; 2. CAPEX = 13; FOM = 11;	The tested CAPEX/FOM pairs are recalculated from the same fixed and capacity-dependent VPP cost components using coordination capacity allocations of 50 and 10 MW, respectively, matching the example reported in the source ⁵⁷ .
DC reversible substation retrofit	CAPEX = 177; FOM = 2.66	1. CAPEX = 152; FOM = 2.28 2. CAPEX = 203; FOM = 3.04	The source reports that engineering and integration costs account for 50–100% of the TCI equipment price ⁵⁹ . The cost input used for comparison uses the midpoint, 75%; the tested bounds use 50% and 100%.
ERES VOM	VOM = 13	1. VOM = 6.5; 2. VOM = 26; 3. VOM = 65	The tested VOM values are 0.5, 2 and 5 times the 13 USD MWh ⁻¹ input used for comparison and are used as stress-test settings.

T2G, VPP, DC and TCI denote Train-to-Grid, virtual power plant, direct current and thyristor line-commutated inverter, respectively. CAPEX, FOM and VOM denote capital expenditure, fixed operation and maintenance, and variable operation and maintenance, respectively. CAPEX and FOM values are expressed in 2025 USD kW⁻¹ and 2025 USD kW⁻¹ yr⁻¹, respectively. VOM is expressed in 2025 USD per MWh of ERES electricity discharged.

The sensitivity analysis comprises 36 T2G perturbation cases, covering two cost settings across 18 region–scenario combinations; 12 Europe-only DC retrofit perturbation cases, covering two cost settings across six European scenarios; and 54 VOM perturbation cases, covering three cost settings across 18 region–scenario combinations. We therefore reoptimize 102 perturbation cases. The 18 previously calculated ERES cases using the cost inputs in Table 1 and Supplementary Table 26 serve as the comparison cases after validation against the associated capacity-expansion outputs, producing 120 unique model-result cases. For each case, we evaluate average annual total system cost savings, annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction. For each metric Y , the percentage change is calculated relative to the value for the same region and scenario in the comparison ERES case using supplementary equation (81).

$$\Delta Y_{r,d,p} = \frac{Y_{r,d,p} - Y_{r,d,\text{ref}}}{|Y_{r,d,\text{ref}}|} \times 100\% \quad (81)$$

where r denotes China, Europe or India; d denotes one of the six combinations of BR or HR with C, M or A; p denotes the tested cost setting; and ref denotes the ERES case with the same r and d using the comparison cost inputs in Table 1 and Supplementary Table 26. For average annual total system cost savings, annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction, a negative percentage change denotes a lower value than in the comparison ERES case, whereas a positive percentage change denotes a higher value.

Sensitivity of system-level outcomes to ERES economic cost assumptions

Supplementary Fig. 18 summarizes the percentage changes in average annual total system cost savings, annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction under the tested T2G coordination system, DC reversible substation retrofit and ERES VOM cost inputs. For each cost group, percentage changes are calculated relative to the metric value in the comparison case for the same region and scenario, as defined below.

T2G coordination system cost. The T2G comparison case uses CAPEX of 5.8 USD kW⁻¹ and FOM of 5.0 USD kW⁻¹ yr⁻¹. The two tested settings use CAPEX of 6.6 USD kW⁻¹ and FOM of 5.7 USD kW⁻¹ yr⁻¹, and CAPEX of 13 USD kW⁻¹ and FOM of 11 USD kW⁻¹ yr⁻¹. The tests cover the 18 combinations formed by China, Europe and India; BR and HR; and C, M and A. CAPEX and FOM are changed jointly because each pair is recalculated from the fixed and capacity-dependent VPP cost components described in the Train-to-Grid coordination system cost section; all other economic and technical inputs are held fixed. All percentage changes in this subsection are calculated relative to the metric value in the T2G comparison case for the same region and scenario.

With T2G CAPEX of 6.6 USD kW⁻¹ and FOM of 5.7 USD kW⁻¹ yr⁻¹, average annual total system cost savings are 1.42–2.68% lower. The percentage changes in annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction range from –0.89% to +0.03% and from –0.23% to +0.43%, respectively.

With T2G CAPEX of 13 USD kW⁻¹ and FOM of 11 USD kW⁻¹ yr⁻¹, average annual total system cost savings are 12.7–24.2% lower. The percentage changes in annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction range from –1.72% to +2.69% and from –0.38% to +0.56%, respectively.

The largest absolute decrease in average annual total system cost savings is US\$0.95 billion yr⁻¹ and occurs in the China HR–A scenario with T2G CAPEX of 13 USD kW⁻¹ and FOM of 11 USD kW⁻¹ yr⁻¹. This decrease equals 24.2% of the value in the T2G comparison case for the China HR–A scenario. With the same tested T2G inputs, the largest absolute difference in annual operational CO₂ emissions reduction is 0.71 Mt CO₂ yr⁻¹ and the largest absolute percentage change is 2.69%; each occurs in the India HR–A scenario. The largest absolute difference in net construction-phase embodied carbon reduction is 0.38 Mt CO₂-eq and the largest absolute percentage change is 0.56%; each also occurs in the India HR–A scenario.

DC reversible substation retrofit cost. The DC retrofit comparison case assumes that engineering and integration costs account for 75% of the TCI equipment price, giving CAPEX of 177 USD kW⁻¹ and FOM of 2.66 USD kW⁻¹ yr⁻¹. The tested settings use the source-reported lower and upper percentages of 50% and 100%. The 50% setting gives CAPEX of 152 USD kW⁻¹ and FOM of 2.28 USD kW⁻¹ yr⁻¹, whereas the 100% setting gives CAPEX of 203 USD kW⁻¹ and FOM of 3.04 USD kW⁻¹ yr⁻¹. The tests cover the six European combinations formed by BR or HR and C, M or A, with the European DC railway share held fixed at 37.35%. All percentage changes in this subsection are calculated relative to the metric value in the DC retrofit comparison case for the same scenario.

When engineering and integration costs account for 50% of the TCI equipment price, average annual total system cost savings are 0.76–1.16% higher. When engineering and integration costs account for 100% of the TCI equipment price, average annual total system cost savings are 0.76–1.16% lower. The largest absolute difference in average annual total system cost savings is US\$0.010 billion yr⁻¹ and occurs in the Europe HR–A scenario under the 100% setting. This difference equals 1.16% of the value in the DC retrofit comparison case for the Europe HR–A scenario.

In the 50% and 100% settings, the largest absolute difference in annual operational CO₂ emissions reduction is 6.7 × 10⁻⁶ Mt CO₂ yr⁻¹ and occurs in the Europe BR–M scenario under the 100% setting. This difference is less than 0.0001% of the value in the DC retrofit comparison case for the Europe BR–M scenario. The largest absolute difference in net

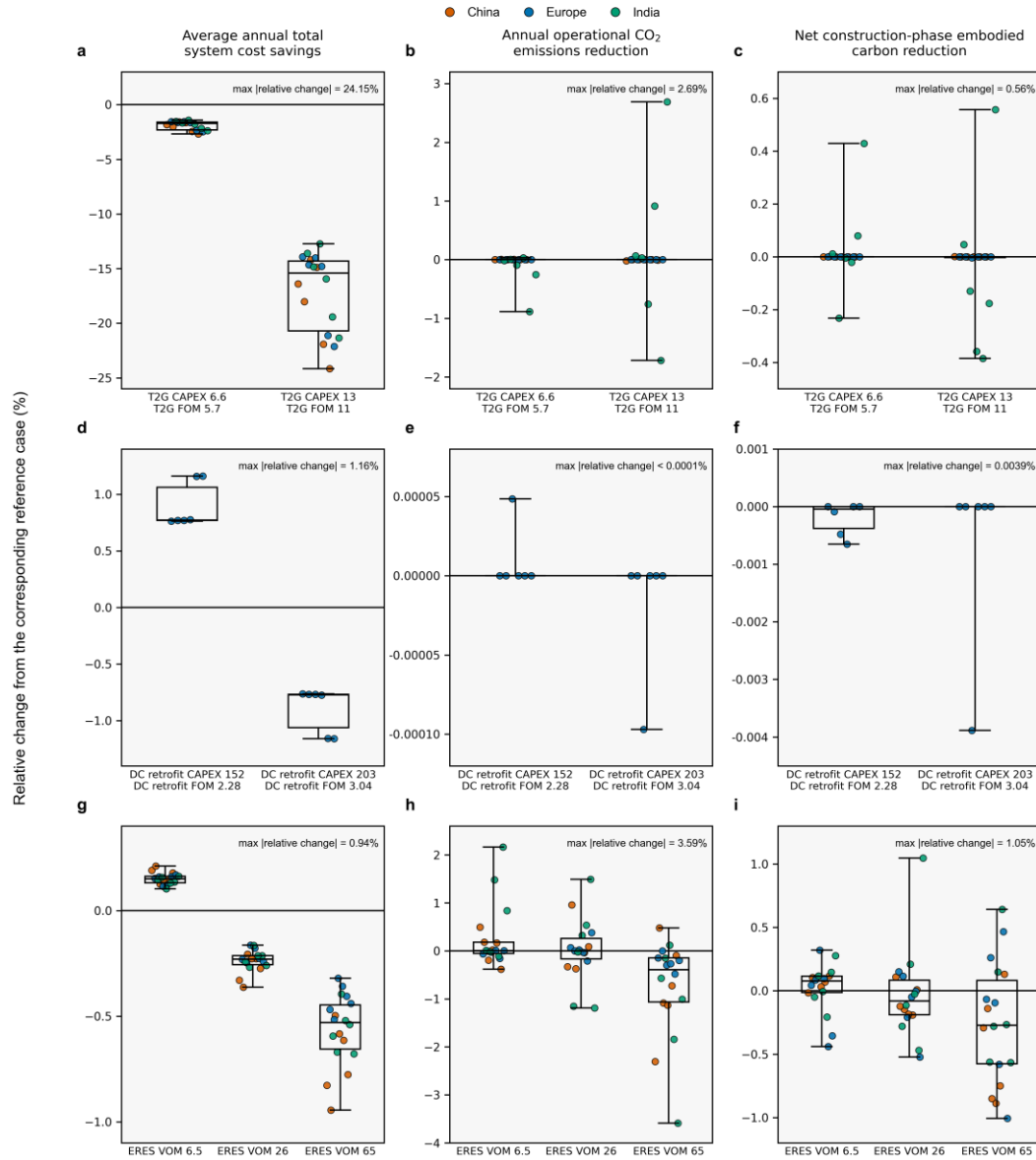
construction-phase embodied carbon reduction is 7.9×10^{-4} Mt CO₂-eq in the Europe BR–M scenario under the 100% setting, equal to 0.0039% of the value in the DC retrofit comparison case for that scenario.

ERES variable operation and maintenance cost. The ERES VOM comparison case uses a VOM of 13 USD per MWh of ERES electricity discharged. The tested VOM inputs are 6.5, 26 and 65 USD MWh⁻¹, equal to half, twice and five times the comparison input, respectively. The tests cover the 18 combinations formed by China, Europe and India; BR and HR; and C, M and A. VOM is varied independently while CAPEX, FOM and all technical parameters are held fixed. All percentage changes in this subsection are calculated relative to the metric value in the ERES VOM comparison case for the same region and scenario.

With a VOM of 6.5 USD MWh⁻¹, average annual total system cost savings are 0.10–0.21% higher. The percentage changes in annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction range from –0.38% to +2.16% and from –0.44% to +0.32%, respectively. With a VOM of 26 USD MWh⁻¹, average annual total system cost savings are 0.16–0.36% lower, while the percentage changes in annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction range from –1.19% to +1.49% and from –0.52% to +1.05%, respectively. With a VOM of 65 USD MWh⁻¹, average annual total system cost savings are 0.32–0.94% lower, while the percentage changes in annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction range from –3.59% to +0.48% and from –1.01% to +0.64%, respectively.

The largest absolute difference in average annual total system cost savings is US\$0.050 billion yr⁻¹ and occurs in the China HR–C scenario with a VOM of 65 USD MWh⁻¹. This difference equals 0.94% of the value in the ERES VOM comparison case for the China HR–C scenario. For annual operational CO₂ emissions reduction, the largest absolute difference is 0.76 Mt CO₂ yr⁻¹ in the China BR–M scenario with a VOM of 65 USD MWh⁻¹, whereas the largest absolute percentage change is 3.59% in the India BR–A scenario with the same VOM. For net construction-phase embodied carbon reduction, the largest absolute difference is 0.85 Mt CO₂-eq in the China BR–A scenario with a VOM of 65 USD MWh⁻¹, whereas the largest absolute percentage change is 1.05% in the India HR–A scenario with a VOM of 26 USD MWh⁻¹. Positive and negative percentage changes occur because annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction are outcomes of the reoptimized investment and dispatch decisions rather than objectives directly minimized by the capacity expansion model.

Among all 102 independently reoptimized perturbation cases, comprising 36 T2G cases, 12 DC retrofit cases and 54 ERES VOM cases, average annual total system cost savings, annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction remain positive. The largest percentage decrease in average annual total system cost savings is 24.2% and occurs in the China HR–A scenario with T2G CAPEX of 13 USD kW⁻¹ and FOM of 11 USD kW⁻¹ yr⁻¹, relative to the T2G comparison case for the China HR–A scenario.



Supplementary Fig. 18 | Sensitivity of system-level outcomes with respect to Electrified Rail-Based Energy Storage (ERES) economic cost assumptions. **a–c**, T2G coordination system costs, with tested settings of CAPEX of 6.6 USD kW⁻¹ and FOM of 5.7 USD kW⁻¹ yr⁻¹, and CAPEX of 13 USD kW⁻¹ and FOM of 11 USD kW⁻¹ yr⁻¹. The T2G comparison case uses CAPEX of 5.8 USD kW⁻¹ and FOM of 5.0 USD kW⁻¹ yr⁻¹. T2G denotes Train-to-Grid; CAPEX, FOM and VOM denote capital expenditure, fixed operation and maintenance, and variable operation and maintenance, respectively; DC denotes direct current; and TCI denotes thyristor line-commutated inverter. **d–f**, DC reversible substation retrofit costs, with tested settings of CAPEX of 152 USD kW⁻¹ and FOM of 2.28 USD kW⁻¹ yr⁻¹, and CAPEX of 203 USD kW⁻¹ and FOM of 3.04 USD kW⁻¹ yr⁻¹. In the two tested settings, engineering and integration costs account for 50% and 100% of the TCI equipment price, respectively. The DC retrofit comparison case assumes 75%, giving CAPEX of 177 USD kW⁻¹ and FOM of 2.66 USD kW⁻¹ yr⁻¹. The DC retrofit tests apply only to Europe. **g–i**, ERES VOM values of 6.5, 26 and 65 USD MWh⁻¹. The ERES VOM comparison case uses 13 USD MWh⁻¹. Within each row, the panels from left to right show percentage changes in average annual total system cost savings, annual operational CO₂ emissions reduction and net construction-phase embodied carbon reduction. Percentage changes in a–c, d–f and g–i are calculated relative to the T2G, DC retrofit and ERES VOM comparison cases, respectively, for the same region and scenario. Each point represents one region–scenario combination. Boxes show the interquartile range, center lines show the median and whiskers show the full range. Zero denotes no change from the applicable comparison case. Each perturbation case is independently reoptimized with all inputs outside the tested cost group held fixed.

ERES technical parameters

The round-trip efficiency of ERES describes the ratio between the electrical energy delivered back to the power system and the electrical energy absorbed from the power system over a complete charge–discharge cycle. For electrochemical storage, this parameter usually represents losses in battery cells, power conversion systems and auxiliary equipment. For ERES, the storage medium is train mechanical energy. The corresponding conversion chain is therefore electrical energy to train mechanical energy during traction, followed by train mechanical energy to electrical energy during regenerative braking. The round-trip efficiency of ERES is consequently determined by the product of traction efficiency and regenerative braking efficiency.

At the railway operation level, these conversion efficiencies are already represented explicitly for each inter-stop train operation. Each ITO is mapped to a train technical parameter set that includes traction efficiency and regenerative braking efficiency. During charge regulation, additional electrical power is converted into mechanical power through the traction efficiency. During discharge regulation, reduced traction demand or regenerative braking output is converted back to electrical power through the regenerative braking efficiency. Therefore, the capacity assessment does not treat ERES as a lossless flexibility resource; conversion losses are embedded in the feasible power and energy deviations derived from the train operation model.

For the capacity expansion model, ERES is represented as a storage-equivalent resource, so an aggregate round-trip efficiency is required. We use the representative traction and regenerative braking efficiencies from the train parameter sets to define this value. The representative traction efficiency and regenerative braking efficiency are both 0.94, yielding the round-trip efficiency in supplementary equation (82).

$$\eta_{\text{ERES}}^{\text{RTE}} = \eta^{\text{T}} \eta^{\text{B}} = 0.94 \times 0.94 \approx 0.88 \quad (82)$$

where $\eta_{\text{ERES}}^{\text{RTE}}$ denotes the ERES round-trip efficiency; η^{T} and η^{B} denote traction efficiency and regenerative braking efficiency, respectively. This aggregate value is used only in the capacity expansion model. The rail-side ERES parameterization still uses the train-specific conversion efficiencies assigned to individual ITOs.

The depth of discharge parameter is used differently from its conventional meaning in battery systems. For electrochemical storage, the depth of discharge is often imposed to avoid excessive material degradation caused by deep charge and discharge cycles. ERES stores energy through train mechanical energy within timetable, speed and power constraints. Its assessed technical energy capacity is therefore not limited by electrochemical degradation, but by the feasible mechanical energy deviation that can be created and recovered during scheduled train operation.

However, the technical energy capacity derived from the regulation optimization represents a boundary value of feasible operation. Two considerations motivate the use of a lower usable energy capacity in the planning model. First, the large-scale ERES assessment uses an energy-oriented representation of train operation, which simplifies the detailed nonlinear train kinetic process. Although this representation is designed to preserve the main mechanical energy balance, a planning model should not dispatch the entire assessed capacity exactly at this boundary. Second, the optimization identifies the maximum feasible regulation capacity under punctuality, speed and power constraints. In practical railway operation, dispatch should retain an operating margin for traffic control, minor timetable deviations, equipment status, protection requirements and modeling uncertainty.

We therefore apply a depth of discharge of 90% to convert the assessed technical energy capacity into the usable ERES energy capacity used in SWITCH, withholding 10% of the assessed technical energy capacity as an operating margin, twice the margin adopted in a reference train operation study², as expressed in supplementary equations (83) and (84).

$$\bar{E}_{r,p,q}^{\text{use}} = \delta^{\text{ERES}} \bar{E}_{r,p,q}^{\text{tech}} \quad (83)$$

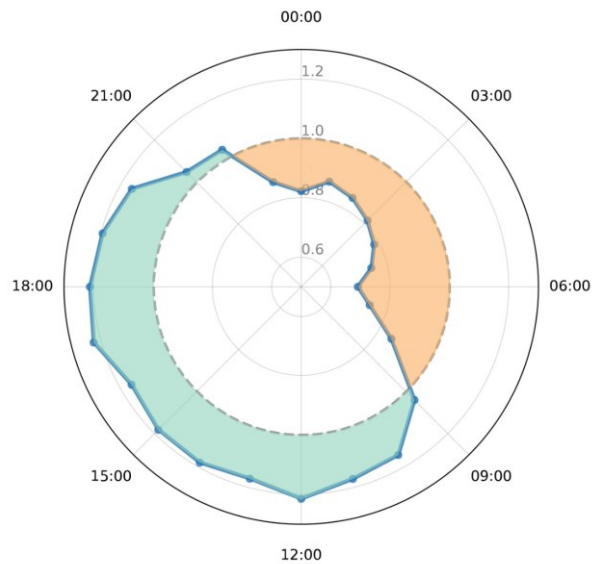
$$\delta^{\text{ERES}} = 0.90 \quad (84)$$

where $\bar{E}_{r,p,q}^{\text{tech}}$ is the technical ERES energy capacity derived from the rail-side assessment for region r , planning period

p and rail development assumption q ; $\bar{E}_{r,p,q}^{\text{use}}$ is the usable energy capacity entering the capacity expansion model; δ^{ERES} is the usable energy fraction. This treatment withholds 10% of the assessed technical energy capacity as an operating margin. It allows ERES to be optimized consistently with other energy storage resources in SWITCH, while avoiding dispatch at the theoretical railway feasibility boundary.

ERES dispatch is further shaped by time-dependent availability profiles derived from railway timetables. These profiles are expressed as relative multipliers around the average available ERES capability. A value of 1 represents the average capacity level used as the benchmark capacity bound, values above 1 indicate hours with railway regulation capability higher than average, and values below 1 indicate hours with capability lower than average. This variation reflects the temporal distribution of train operations, admissible regulation windows and electromechanical power capacity. In the capacity expansion model, the power and energy bounds in each operating hour are obtained by multiplying the benchmark ERES capacity bounds by the corresponding temporal availability coefficient.

Supplementary Fig. 19 reports the timetable-derived ERES temporal availability profiles used in the planning model. These profiles convert the benchmark ERES capacity bounds into time-varying bounds for hourly dispatch and equivalent energy state constraints.



Supplementary Fig. 19 | Temporal availability profile of Electrified Rail-Based Energy Storage (ERES). The blue line shows the hourly multiplier applied to the benchmark ERES capacity bounds. The grey dashed circle denotes the average multiplier of 1. Orange and green shading indicate hours below and above this level, respectively.

Supplementary Method 5. Energy storage deployment changes and construction-phase embodied carbon accounting

Purpose and boundary

This section describes how energy storage deployment changes induced by ERES are converted into construction-phase embodied carbon impacts. The analysis is performed based on the results of electricity system capacity expansion planning.

The embodied carbon results are distinct from the operational CO₂ emissions derived from the power system optimization. Operational emissions are calculated from fossil-fuel electricity generation and fuel-specific emission factors. By contrast, the embodied carbon accounting in this section quantifies cradle-to-gate emissions associated with the construction of storage technologies, including material production, manufacturing and auxiliary components within the available data boundary.

The energy storage technologies considered in this accounting are the same as those represented in the capacity expansion model: battery storage, compressed air energy storage, pumped hydro storage and hydrogen-based storage. Their deployment changes are derived from the optimized model outputs, and their construction-phase carbon impacts are calculated using technology-specific embodied carbon factors.

Changes in energy storage deployment

For each storage technology s , region r , base scenario ω and representative pathway outcome q , the change in cumulative newly built storage power capacity is calculated using supplementary equation (85).

$$\Delta C_{s,r,\omega,q}^P = C_{s,r,\omega,q}^{P,\text{new,ERES}} - C_{s,r,\omega,q}^{P,\text{new,base}} \quad (85)$$

where $C_{s,r,\omega,q}^{P,\text{new,ERES}}$ is the cumulative newly built power capacity of storage technology s in the ERES case, and $C_{s,r,\omega,q}^{P,\text{new,base}}$ is the corresponding cumulative newly built power capacity in the no-ERES baseline. The cumulative capacity is calculated across the planning periods represented in the model.

Negative values of $\Delta C_{s,r,\omega,q}^P$ indicate reduced construction of storage technology s after ERES is introduced. Positive values indicate additional construction. This metric describes an endogenous investment response of the capacity expansion model, as the storage investment is optimized jointly with generation, transmission, dispatch and ERES deployment under each scenario setting.

Embodied carbon factors for energy storage technologies

The construction-phase embodied carbon impact is calculated using technology-specific cradle-to-gate embodied carbon factors. The factors are expressed on a power capacity basis, kg CO₂-eq kW⁻¹, to match the storage deployment changes in newly built power capacity.

Supplementary Table 27. Cradle-to-gate embodied carbon factors for energy storage technologies

Technology	Storage duration	Carbon factor (kg CO ₂ -eq kW ⁻¹)
Battery storage ⁷³	4 h	547.0
Compressed air energy storage ⁷⁴	10 h	475.5
Pumped hydro storage ⁷⁵	15.5 h	586.3
Hydrogen-based storage ⁷³	24 h	821.3

For each storage technology, the same embodied carbon factor is used for China, Europe and India.

Embodied carbon impacts of energy storage deployment

For each storage technology, the construction-phase embodied carbon impact associated with its deployment change is calculated using supplementary equation (86).

$$\Delta\text{GHG}_{s,r,\omega,q}^{\text{storage}} = \text{CF}_s \Delta C_{s,r,\omega,q}^{\text{P}} \quad (86)$$

where CF_s is the cradle-to-gate embodied carbon factor of storage technology s . The net embodied carbon impact from energy storage construction is then calculated using supplementary equation (87).

$$\Delta\text{GHG}_{r,\omega,q}^{\text{storage}} = \sum_{s \in S} \text{CF}_s \Delta C_{s,r,\omega,q}^{\text{P}} \quad (87)$$

where S includes battery storage, pumped hydro storage, compressed air energy storage and hydrogen-based storage. Under this definition, negative values denote avoided embodied emissions from reduced construction, whereas positive values denote additional embodied emissions from increased construction.

ERES retrofit embodied carbon

ERES retrofit embodied carbon is accounted for as a separate term. In this study, the quantified retrofit embodied carbon is applied to DC ERES, because additional reversible substation equipment is required when DC traction supply systems based on unidirectional rectifiers are retrofitted to enable reverse power export to the upstream electricity system.

The DC ERES retrofit embodied carbon factor, denoted by CF_{ERES}^{DC} , is set to approximately 44 kg CO₂-eq kW⁻¹⁷⁶. The ERES retrofit embodied carbon is calculated using supplementary equation (88).

$$GHG_{r,\omega,q}^{ERES} = CF_{ERES}^{DC} C_{ERES,r,\omega,q}^{P,DC,retrofit} \quad (88)$$

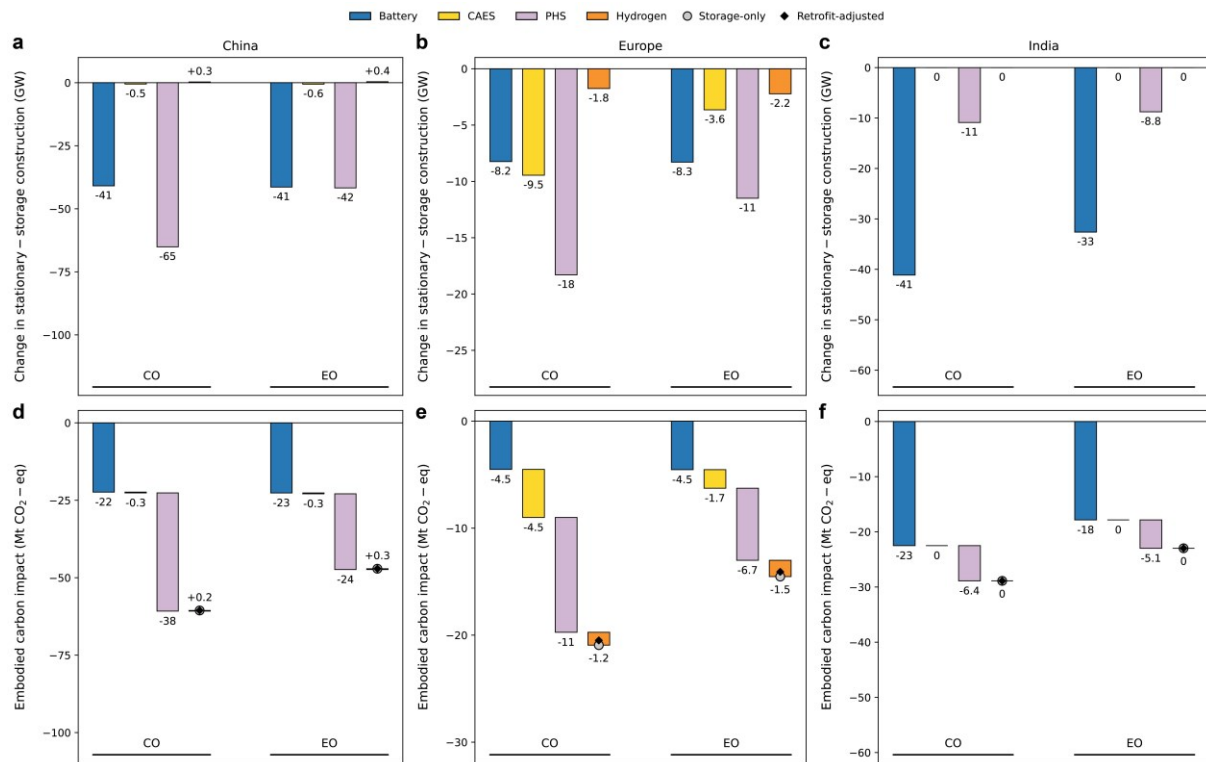
where $C_{ERES,r,\omega,q}^{P,DC,retrofit}$ is the deployed power capacity of DC ERES projects associated with existing DC railway systems that require a reversible substation retrofit. The net embodied carbon impact is calculated using supplementary equation (89).

$$\Delta GHG_{r,\omega,q}^{net} = \Delta GHG_{r,\omega,q}^{storage} + GHG_{r,\omega,q}^{ERES} \quad (89)$$

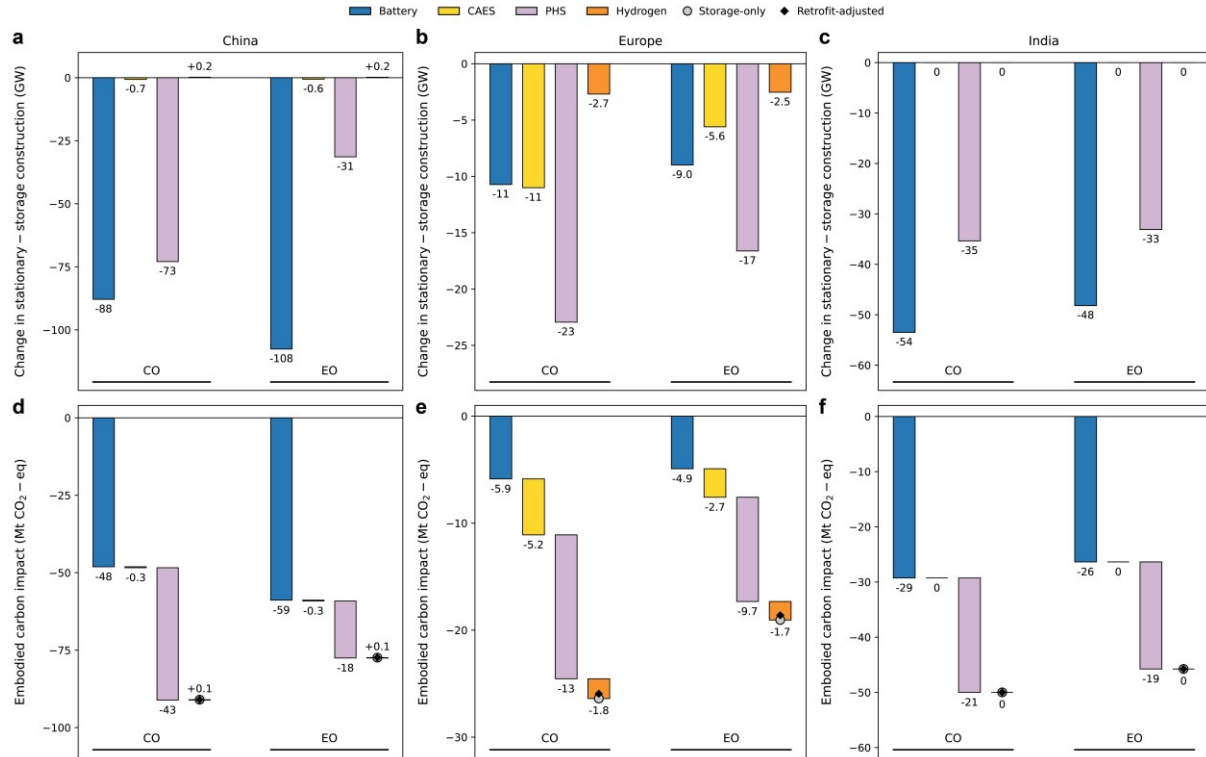
The sign convention is the same as in the Embodied carbon impacts of energy storage deployment section. Avoided embodied emissions from lower storage construction are negative, and ERES retrofit embodied carbon is positive. Therefore, a negative value of $\Delta GHG_{r,\omega,q}^{net}$ indicates that the ERES case still produces a net construction-phase embodied carbon reduction after accounting for the quantified retrofit embodied carbon. This value corresponds to the black diamond markers in Fig. 7d–f.

The embodied carbon of the T2G coordination system retrofit is not quantified separately. This retrofit mainly involves secondary equipment for metering, communication, control and coordination⁵⁷, rather than primary power conversion equipment. Its embodied carbon is therefore expected to be much smaller than that of power electronics, storage sections or reversible substation equipment. Moreover, published embodied-carbon inventory data for T2G retrofits are not yet available. We therefore exclude this component from the quantitative embodied carbon accounting and identify it as a limitation of the embodied-carbon accounting boundary.

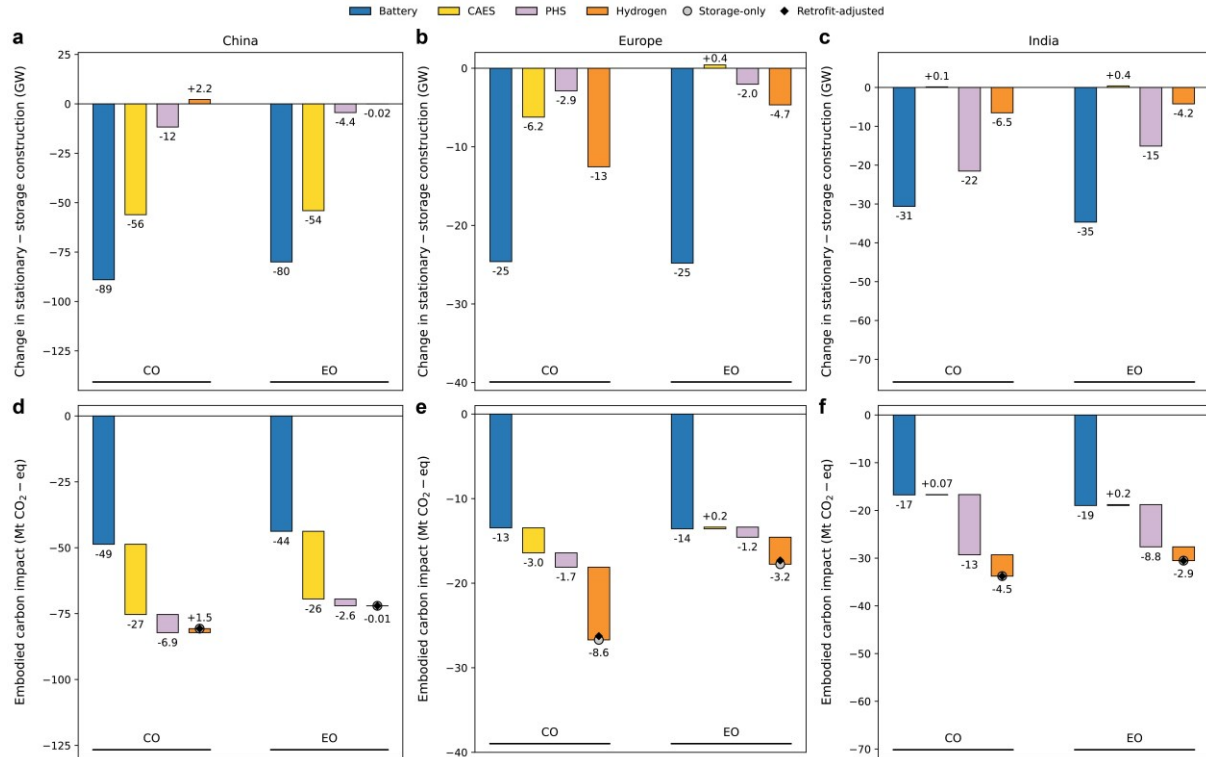
Supplementary outputs across scenarios



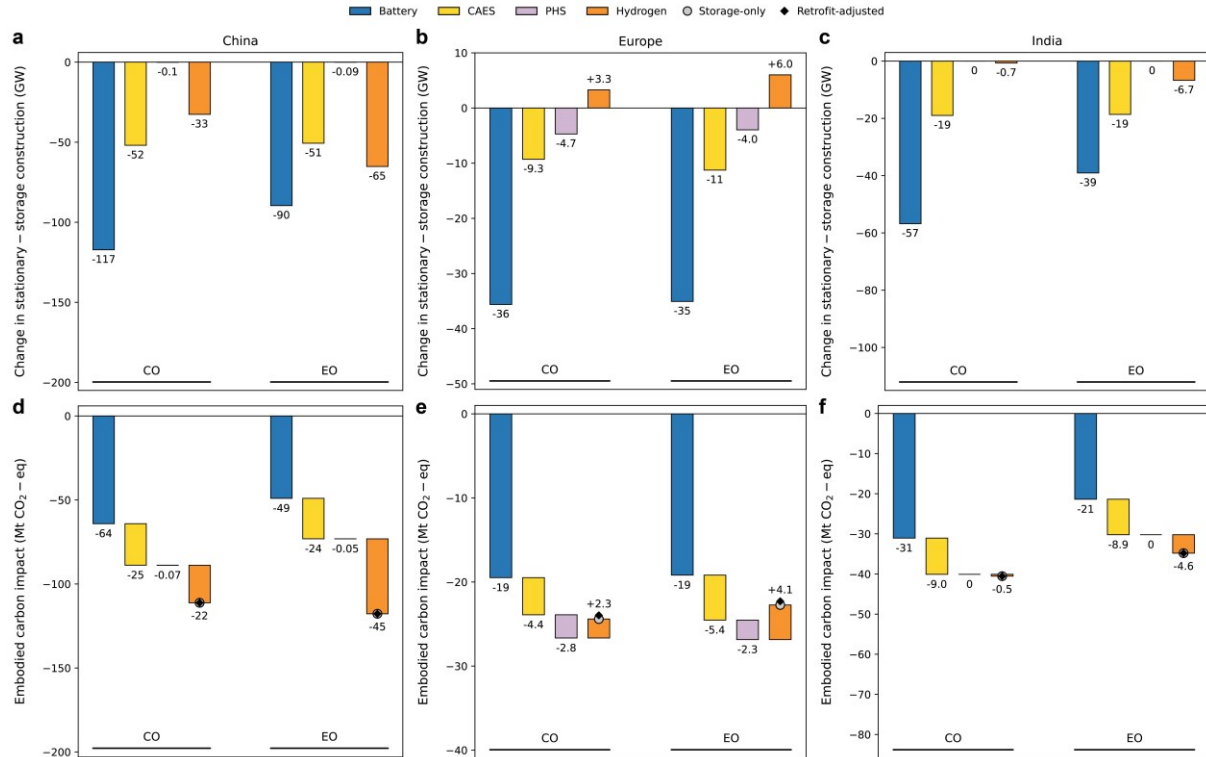
Supplementary Fig. 20 | Energy storage deployment changes and embodied carbon implications in BR-C scenarios. **a-c,** Changes in cumulative newly built storage power capacity relative to the corresponding baseline under CO and EO pathways in China, Europe and India, respectively. BR-C combines the base rail scenario with the conservative technology innovation trajectory. CO and EO denote cost-oriented and emission-oriented pathway outcomes, respectively. CAES and PHS denote compressed-air energy storage and pumped-hydro storage, respectively. Negative values indicate reduced construction with the introduction of Electrified Rail-Based Energy Storage (ERES), whereas positive values indicate additional deployment. **d-f,** Cumulative cradle-to-gate embodied carbon impacts over the planning horizon associated with the storage capacity changes in a-c, respectively. Negative values denote avoided embodied emissions from reduced construction, whereas positive values indicate additional embodied emissions from increased construction. Circle markers denote the carbon impact summed over the four storage technologies. Black diamonds denote the net carbon impact after accounting for ERES retrofit embodied carbon.



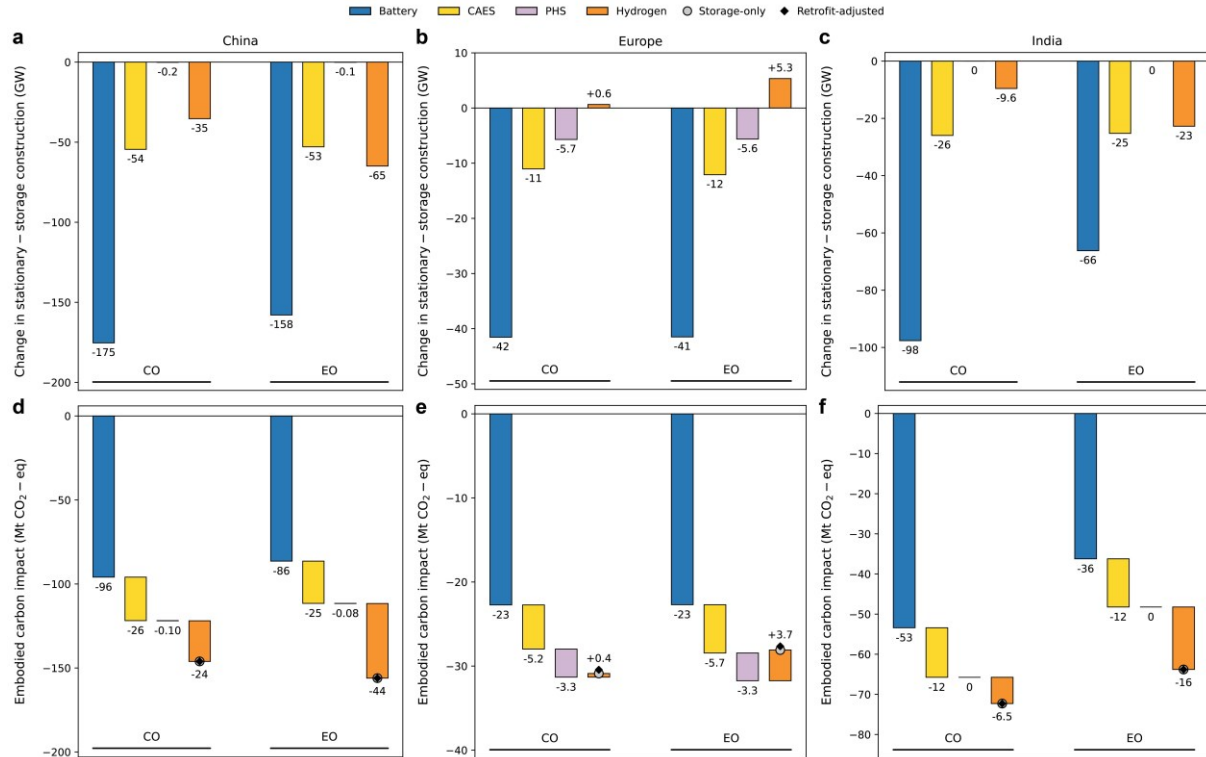
Supplementary Fig. 21 | Energy storage deployment changes and embodied carbon implications in HR-C scenarios. a–c, Changes in cumulative newly built storage power capacity relative to the corresponding baseline under CO and EO pathways in China, Europe and India, respectively. HR-C combines the high rail scenario with the conservative technology innovation trajectory. CO and EO denote cost-oriented and emission-oriented pathway outcomes, respectively. CAES and PHS denote compressed-air energy storage and pumped-hydro storage, respectively. Negative values indicate reduced construction with the introduction of Electrified Rail-Based Energy Storage (ERES), whereas positive values indicate additional deployment. **d–f,** Cumulative cradle-to-gate embodied carbon impacts over the planning horizon associated with the storage capacity changes in a–c, respectively. Negative values denote avoided embodied emissions from reduced construction, whereas positive values indicate additional embodied emissions from increased construction. Circle markers denote the carbon impact summed over the four storage technologies. Black diamonds denote the net carbon impact after accounting for ERES retrofit embodied carbon.



Supplementary Fig. 22 | Energy storage deployment changes and embodied carbon implications in BR-M scenarios. **a–c,** Changes in cumulative newly built storage power capacity relative to the corresponding baseline under CO and EO pathways in China, Europe and India, respectively. BR-M combines the base rail scenario with the moderate technology innovation trajectory. CO and EO denote cost-oriented and emission-oriented pathway outcomes, respectively. CAES and PHS denote compressed-air energy storage and pumped-hydro storage, respectively. Negative values indicate reduced construction with the introduction of Electrified Rail-Based Energy Storage (ERES), whereas positive values indicate additional deployment. **d–f,** Cumulative cradle-to-gate embodied carbon impacts over the planning horizon associated with the storage capacity changes in a–c, respectively. Negative values denote avoided embodied emissions from reduced construction, whereas positive values indicate additional embodied emissions from increased construction. Circle markers denote the carbon impact summed over the four storage technologies. Black diamonds denote the net carbon impact after accounting for ERES retrofit embodied carbon.



Supplementary Fig. 23 | Energy storage deployment changes and embodied carbon implications in BR-A scenarios. **a-c**, Changes in cumulative newly built storage power capacity relative to the corresponding baseline under CO and EO pathways in China, Europe and India, respectively. BR-A combines the base rail scenario with the advanced technology innovation trajectory. CO and EO denote cost-oriented and emission-oriented pathway outcomes, respectively. CAES and PHS denote compressed-air energy storage and pumped-hydro storage, respectively. Negative values indicate reduced construction with the introduction of Electrified Rail-Based Energy Storage (ERES), whereas positive values indicate additional deployment. **d-f**, Cumulative cradle-to-gate embodied carbon impacts over the planning horizon associated with the storage capacity changes in a-c, respectively. Negative values denote avoided embodied emissions from reduced construction, whereas positive values indicate additional embodied emissions from increased construction. Circle markers denote the carbon impact summed over the four storage technologies. Black diamonds denote the net carbon impact after accounting for ERES retrofit embodied carbon.



Supplementary Fig. 24 | Energy storage deployment changes and embodied carbon implications in HR-A scenarios. a–c, Changes in cumulative newly built storage power capacity relative to the corresponding baseline under CO and EO pathways in China, Europe and India, respectively. HR-A combines the high rail scenario with the advanced technology innovation trajectory. CO and EO denote cost-oriented and emission-oriented pathway outcomes, respectively. CAES and PHS denote compressed-air energy storage and pumped-hydro storage, respectively. Negative values indicate reduced construction with the introduction of Electrified Rail-Based Energy Storage (ERES), whereas positive values indicate additional deployment. **d–f,** Cumulative cradle-to-gate embodied carbon impacts over the planning horizon associated with the storage capacity changes in a–c, respectively. Negative values denote avoided embodied emissions from reduced construction, whereas positive values indicate additional embodied emissions from increased construction. Circle markers denote the carbon impact summed over the four storage technologies. Black diamonds denote the net carbon impact after accounting for ERES retrofit embodied carbon.

Supplementary Method 6. Simulation of ancillary service and railway line operation

Regional ancillary service case setup

The regional ancillary service case is applied to a representative power system disturbance according to the Jinping–Sunan incident⁷⁷. The power system is represented using a first-order system frequency response model, which reduces the regional grid to an equivalent system describing the average frequency deviation after a power disturbance. The first-order system frequency response model is expressed in supplementary equations (90) and (91).

$$2H \frac{d\Delta f(t)}{dt} + D\Delta f(t) = P_e(t) - P_m(t) \quad (90)$$

$$T \frac{dP_m(t)}{dt} + P_m(t) = \frac{1}{R} \Delta f(t) + P_{SP}(t) \quad (91)$$

where Δf denotes the system frequency deviation; D , H , R and T represent the damping factor, inertia constant, governor droop and governor reheat time constant, respectively; P_m , P_e and P_{SP} represent turbine mechanical power, generator electrical load power and incremental power set point, respectively. The parameters are identified from the recorded frequency curve of the incident using the System Identification Toolbox in MATLAB 2024a and calibrated with empirical system parameters.

The comparison in Fig. 8c is performed between two cases with the same disturbance, system configurations and initial operating conditions. In the reference case, the disturbance is balanced by primary and secondary control. In the ERES case, the same disturbance and system parameters are retained, and the aggregate ERES response derived from the East China railway assessment is introduced as an additional regulation resource.

Positive ERES power denotes additional electricity absorption by trains relative to the scheduled baseline, corresponding to charging. Negative ERES power denotes reduced net traction demand or regenerative output relative to the scheduled baseline, corresponding to discharging. The regional response in Fig. 8c therefore represents the aggregate effect of all participating East China trains, rather than the response of only the representative line shown in Fig. 8d–f.

Supplementary Table 28. Configuration of the regional ancillary service case.

Parameter	Value	Units
System configuration		
Damping factor	2.85	
inertia constant	11.5	sec
governor droop	0.3	
governor reheat time constant	16	sec
Start time of secondary response	140	sec
Ramp rate	140.7	MW min ⁻¹
Normal frequency	50	Hz
Incident data		
Total load	138	GW
Power loss	4.9	GW
Electrified Rail-Based Energy Storage regulation		
Discharge power	1.61	GW
Recharge power	0.36	GW
Discharge duration	5	min
Recharge duration	25	min

Representative line, timetable and train fleet

The railway line operation case uses two parallel electrified railway lines within the East China railway system. The first line is the East China portion of the Shanghai–Kunming High-speed Railway, which carries high-speed electric multiple unit trains. The second line is the parallel East China portion of the Shanghai–Kunming Railway, which carries electric locomotive-hauled trains. These two lines are selected to include different operating patterns, train types and speed ranges within the same regional railway system.

The line timetable is processed using the ITO record construction described in Supplementary Note 1. Each scheduled movement from a departure stop to the next scheduled stop is treated as one inter-stop train operation. Intermediate stations passed without scheduled stopping do not create additional inter-stop train operations. Each inter-stop train operation is assigned to its corresponding train technical parameter set and line constraints, including train mass, rated traction power, traction force, braking force, traction efficiency, regenerative braking efficiency, line distance and speed limit.

Supplementary Table 29. Simulated inter-stop train operations in the representative line case.

Railway line	Speed limit (km h ⁻¹)	Departure time (UTC+8:00)	Arrival time (UTC+8:00)	Travel distance (km)
Shanghai– Kunming High-speed Railway	310	20:45	22:48	520
	310	19:55	22:38	658
	310	20:46	22:35	469
	310	21:38	23:04	343
	350	21:49	23:14	336
	350	21:49	22:25	108
	350	21:38	22:11	108
	350	21:44	22:16	108
Shanghai– Kunming Railway	120	21:34	01:02 (next day)	279
	120	20:40	23:45	291
	120	21:17	23:08	141
	120	21:11	23:02	141
	120	21:28	22:43	95
	160	21:37	22:49	141
	160	21:37	22:49	141
	160	21:39	22:42	132

UTC denotes Coordinated Universal Time.

ITO kinetic simulation

The railway line operation case is simulated using detailed train kinetic ODEs with explicit traction, braking, resistance, power and speed constraints. The ERES power commands for ITOs are obtained using the same energy-oriented regulation optimization as in the ERES capacity evaluation.

For each train, the scheduled trajectory is first calculated according to the timetable, line distance, speed limit and train technical parameters. The regulated trajectory is then obtained by adjusting the train control trajectory to follow the ERES power command by minimizing the squared deviation between the realized electrical power change and the requested power command, while satisfying the same timetable and physical constraints. The scheduled arrival time is retained as a hard constraint. The regulated trajectory must also remain within the line speed limit and the train traction and braking power envelopes. The optimization is solved iteratively to reduce the mismatch between the time-based power command and the position-based train trajectory², and the ITO-level command is also refined to improve the agreement between the realized and requested power response.

$$\min_{u_I^n(t), u_B^n(t)} \int_{\Delta t_{\text{adm},s}^n}^{\Delta t_{\text{adm},e}^n} (\Delta P_{\text{sim}}^n(t) - \Delta P_e^n(t))^2 dt \quad (92)$$

$$\Delta P_e^n(t) = \begin{cases} \Delta P_e^{n,\Delta t_i}, & \Delta t_i \leq t < \Delta t_{i+1}, \Delta t_i \in T^n \\ 0, & \text{otherwise} \end{cases} \quad (93)$$

$$0 \leq v_{\text{sim}}^n(t) \leq v_{\text{lim}}^n \quad (94)$$

$$v_{\text{sim}}^n(\Delta t_{\text{adm},s}^n) = v_{\text{sch}}^n(\Delta t_{\text{adm},s}^n) \quad (95)$$

$$v_{\text{sim}}^n(\Delta t_{\text{adm},e}^n) = v_{\text{sch}}^n(\Delta t_{\text{adm},e}^n) \quad (96)$$

$$x_{\text{sim}}^n(\Delta t_{\text{adm},s}^n) = x_{\text{sch}}^n(\Delta t_{\text{adm},s}^n) \quad (97)$$

$$x_{\text{sim}}^n(\Delta t_{\text{adm},e}^n) = x_{\text{sch}}^n(\Delta t_{\text{adm},e}^n) \quad (98)$$

where $\Delta t_{\text{adm},s}^n$ and $\Delta t_{\text{adm},e}^n$ denote the discretized start and end times of the admissible regulation window of ITO n . $\Delta P_{\text{sim}}^n(t)$ represents the electric power change in the adjusted trajectory simulation; $\Delta P_e^n(t)$ denotes the power regulation command of ERES; $x_{\text{sim}}^n(t)$ and $v_{\text{sim}}^n(t)$ represent the position and speed of ITO n at time t , respectively, which are calculated from the ODEs; $x_{\text{sch}}^n(t)$ and $v_{\text{sch}}^n(t)$ are scheduled position and speed, respectively.

Interpretation and limitations

The representative ERES demonstration case supports the operational plausibility of ERES under railway operating constraints. It shows how a regional ERES response can be linked to train trajectory adjustment, and how the selected line can follow the requested regulation command while retaining scheduled arrival times and respecting speed and power limits.

This case does not represent a demonstration of deployability on every railway line worldwide. Practical deployment would still require local traction power studies, voltage and power quality assessment, protection coordination, communication system design and operating procedures between railway dispatch and power system dispatch. These issues depend on local traction supply topology, substation configuration, train density, operating rules and grid connection conditions. The representative case therefore complements the planning-level capacity assessment by demonstrating executable train trajectories in one regional example, while local engineering studies and pilot line demonstrations remain necessary before practical deployment.

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