

Forecasting and Low-Carbon Demand Response Scheduling of Crane-Group Station-Service Loads for Grid-Friendly Hydropower Station Operation

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Abstract

Net power injection at the point of common coupling (PCC) is an important indicator of grid-friendly hydropower operation. High-power station-service equipment may consume regulation margin and cause short-term power disturbances if it is not coordinated with unit dispatch and automatic generation control (AGC) tracking. This paper models hydropower-station crane groups as safety-bounded, forecastable, and dispatchable station-service flexibility resources, and proposes a forecast-embedded low-carbon demand response framework. The framework develops a PCC-coupled station-service model, uses phase-aware probabilistic forecasting to generate crane consumption templates, regeneration templates, and uncertainty intervals, and coordinates rigid, semi-flexible, and flexible crane tasks through rolling mixed-integer optimization to reduce station-service peaks, PCC tracking deviations, and carbon-opportunity costs. A station-oriented digital validation case shows that, while satisfying all task deadlines and safety constraints, the proposed method reduces the representative-day station-service peak by 16.1%, PCC RMSE by 55.1%, and carbon-opportunity cost by 29.7%, and increases regenerative-energy utilization from 54.8% to 86.8%, compared with earliest-start scheduling. An archive replay on an actual hydropower station with a 15.00 MW installed crane fleet then shows that start-time shifting remains available under that station's work-order windows. On a high-duty maintenance day the representative-day peak falls by 15.4%, and over 20 high-duty days the mean peak falls by 17.3%, while regenerative utilization rises from 65.6% to 90.0%. The two evaluations indicate that crane groups at stations that issue work-order-based crane tasks with usable flexibility windows can be co-scheduled as station-service flexibility resources with phase structure, safety boundaries, and temporal regulation value. The reported magnitudes are those of the two cases and are not claimed for other layouts.

Keywords: hydropower station, crane group, station-service load, probabilistic forecasting, low-carbon demand response, regenerative energy

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1. Introduction

1.1. Background and motivation

Grid-friendly hydropower stations manage generation-side output together with station-service-side disturbances. With higher penetration of wind and photovoltaic generation, hydropower operation is evaluated

not only by annual energy production but also by short-term balancing, ramping and reserve provision, and by the smoothness of PCC net injection [1, 2]. Turbine-generator dispatch, reservoir operation, pumped storage and automatic generation control have been examined in this context. The quantity observed by the grid is the PCC net injection formed by unit generation, station-service consumption, regenerative energy and local storage. If internal station-service loads are not predicted and coordinated, they consume regulation

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margin and appear as disturbances on the net-output trajectory.

Crane groups are a class of station-service loads in hydropower stations. Large stations typically include powerhouse bridge cranes, dam-crest gantry cranes, intake gantry cranes, tailwater gantry cranes, fixed gate hoists, and auxiliary hoisting devices. These devices are triggered by maintenance tasks, gate-operation procedures, unit start-stop preparation, emergency isolation, material transfer, and flood-control support. Unlike pumps, fans, or lighting loads, crane-group loads are intermittent, task-driven, high-power blocks whose electrical effects are concentrated in short intervals. When crane operations overlap with unit start-up, cooling-water pumps, governor oil systems, air compressors, or AGC regulation, they increase station-service peak demand and reduce the smoothness of PCC net injection.

Crane-group operation is governed by motion sequences, equipment occupation and work-order priority, together with gate-safety and personnel-safety procedures. Some tasks must be executed immediately; others may be shifted only within a narrow window, or may be delayed, advanced or executed at reduced speed. Lowering and braking phases may produce regenerative energy, which is absorbed only when local loads, converters or storage retain unused capacity. The resulting problem is to forecast task-level power, uncertainty and regenerative intervals, and to adjust start times and modes only within the safety-permitted range.

1.2. Related work and research gap

Related work comprises four areas: crane-load forecasting and energy management; probabilistic industrial-load forecasting and demand response; industrial flexibility for grid services; and low-carbon demand response.

Electrified rubber-tyred gantry (RTG) crane loads are highly volatile, weakly seasonal, and more difficult to predict than conventional low-voltage loads; exogenous operational variables such as crane moves and container weight improve day-ahead accuracy, while operator behavior and trajectory choice remain a source of uncertainty [3]. Hydropower-station crane power is likewise affected by task type, operating phase, and operation process. Port-crane studies address port substations and logistics rather than AGC tracking, gate-operation safety, unit start-stop coordination, or station-service transformer limits.

Phase-dependent energy use and regenerative potential during lowering are documented for RTG and overhead cranes [4–7]. Hybrid power trains and receding-horizon or stochastic storage control reduce peak demand when the crane work sequence is given

[8–12]; that storage-only, receding-horizon design is used as a literature baseline in Section 5. Trajectory optimization and energy-efficient command shaping change crane energy at the motion-control level [13–15]. Energy-aware quay-crane, berth, and automated-storage scheduling move tasks inside logistics windows [16–21], and robust RTG control preserves motion feasibility [22]. These models do not represent hydropower-station safety procedures, station-service limits, AGC tracking, or PCC net-injection performance.

Probabilistic industrial-load forecasts supply interval information when volatility and heteroscedasticity are strong [23]. Demand-response studies classify regulation into curtailment, modulation, and shifting; load-block shifting applies when start times can move but the internal profile cannot be reshaped arbitrarily [2, 24, 25]. A crane task has the same structure: the start time is adjustable within a window, while hoisting, traveling, lowering, and braking keep physical order. A point-forecast implementation of that load-block formulation is used as a literature baseline in Section 5. Existing load-block and industrial-frequency-regulation studies mainly treat customer-side offers, system-level demand response, or continuous process loads with thermal inertia [26]. They rarely include crane occupation conflicts, safety-critical gate priorities, regenerative absorption, or the link between station-service load and hydropower net injection.

Load shifting guided only by electricity price need not reduce carbon; the effect depends on the marginal generation displaced or induced [27, 28]. Marginal emission factors have been used to weight demand-side resources by that carbon effect [28, 29], and a carbon-blind, peak-oriented counterpart is required alongside a carbon-weighted schedule [26–28]. Internal station-service consumption at a hydropower plant reduces low-carbon export and may induce higher-emission compensation on the external system, so the carbon-opportunity cost of a crane-group schedule depends on load timing, regenerative absorption, and the resulting net-power trajectory.

The remaining gap is a forecast-embedded scheduling formulation that links task uncertainty with a safety-feasible window, station-service electrical limits, regenerative-energy absorption, PCC tracking and a low-carbon timing term. Crane studies have not addressed hydropower PCC coupling or safety-critical gate tasks. Industrial forecasting and demand-response studies have not represented crane phase structure, occupation or regenerative utilization. Hydropower scheduling has rarely treated station-service crane groups as controllable resources. Carbon-aware demand response has not been connected to hydropower work-order tasks or to AGC-related net-output quality.

1.3. Approach and contributions

The scheduling inputs are task-level consumption templates, regenerative intervals and peak-risk windows, together with forecast uncertainty—not a point forecast of the aggregate station-service load. A start time and mode may be chosen only when they satisfy the release and deadline, the precedence and occupation rules, and the safety class. The rolling objective accounts for the station-service peak and the PCC residual, together with regenerative utilization and carbon-opportunity cost; rigid safety tasks remain fixed. Maintenance lifting, emergency gate operation and routine material transfer can have similar electrical magnitude and still differ in permission, delay tolerance and priority.

The framework collects multi-source operating data and task-plan information from crane control systems, variable-frequency drives, station-service meters, SCADA, AGC records, gate-operation logs, and maintenance work orders. A phase-aware probabilistic forecasting model converts these data into scheduling-ready templates. A rolling mixed-integer model then coordinates rigid, semi-flexible, and flexible crane tasks with regenerative-energy absorption and optional station-service storage.

The main contributions are as follows.

First, hydropower-station crane groups are formulated as safety-bounded station-service flexibility resources and represented as internally ordered load blocks. Tasks are classified as rigid, semi-flexible, or flexible. Release times, deadlines, alternative execution modes, precedence, equipment occupation, and delay penalties define the feasible start set. Demand response is introduced only inside that set. The electrical boundary then maps the resulting crane power onto the station-service peak, the PCC net injection and the recovered regeneration.

Second, a phase-aware probabilistic forecasting layer estimates task-level consumption and regenerative intervals and provides peak-risk windows and uncertainty envelopes. On the test set the scheduling residuals are set by short-time peaks, not by daily energy.

Third, a rolling mixed-integer objective penalizes the station-service peak and the PCC tracking residual, and it also penalizes regenerative curtailment, carbon-opportunity cost and task delay. The formulation is evaluated on a station-oriented digital validation case against the earliest-start baseline and three literature-grounded controls: receding-horizon ESS dispatch with a fixed crane sequence [8–10], point-forecast load-block shifting [2, 16, 25], and carbon-blind grid-friendly scheduling [26, 28]. Results with and without a station-service buffer are reported separately.

Fourth, a station-oriented digital validation case is designed for method evaluation, and the same formulation is then instantiated in an archive replay on an

actual hydropower station. The design case isolates forecasting accuracy, peak reduction, tracking residuals, carbon-opportunity cost, regenerative utilization and task feasibility. The actual-station replay uses a 15.00 MW installed fleet as recorded, and reports the station-service peak and regenerative utilization on high-duty maintenance days.

Section 2 describes the crane-group system, the station-service electrical boundary and the task classes. Section 3 presents the phase-aware probabilistic forecasting model. Section 4 formulates the rolling demand-response model. Section 5 reports the digital validation case, the literature-grounded baselines, the ablation and sensitivity tests, and the actual-station archive replay. Section 6 states the work-process conditions under which the same formulation can be instantiated. Section 7 concludes the paper.

2. System modeling and task-level formulation

Crane-group scheduling must preserve both the electrical boundary and the operational boundary. The electrical boundary determines how crane-group station-service loads change PCC net injection. The operational boundary determines that tasks can only be shifted within the safety-preserving domain allowed by maintenance plans, gate-operation rules, work-zone access, and equipment occupation.

2.1. PCC-coupled station-service load boundary

The PCC boundary brings crane-group station-service loads into the evaluation of grid-friendly hydropower operation. A hydropower station is usually dispatched through turbine-generator output, but the grid observes PCC net injection. Even when the units themselves follow AGC instructions, a short hoisting peak can reduce net delivered power. The station-level active-power boundary, tracking residual, and ramp are

$$\begin{cases} p_t^{\text{PCC}} = p_t^{\text{unit}} - p_t^{0,\text{aux}} - p_t^{\text{cg}} + p_t^{\text{ra}} + p_t^{\text{ESS}} \\ e_t^{\text{PCC}} = p_t^{\text{PCC}} - p_t^{\text{ref}} \\ \Delta p_t^{\text{PCC}} = p_t^{\text{PCC}} - p_{t-1}^{\text{PCC}} \end{cases} \quad (1)$$

In (1), p_t^{unit} is the aggregate unit output, $p_t^{0,\text{aux}}$ is the ordinary station-service load excluding crane groups, p_t^{cg} is crane-group active consumption, p_t^{ra} is directly absorbed or fed-through regenerative power, and p_t^{ESS} is the net ESS discharge. The residual and ramp connect an internal station-service action to the grid-facing tracking and ramping quality.

This boundary also defines the role of crane-group demand response. The scheduling objective adjusts the timing of task phases so that high-consumption intervals avoid station-service peaks or AGC-sensitive periods, and regenerative intervals

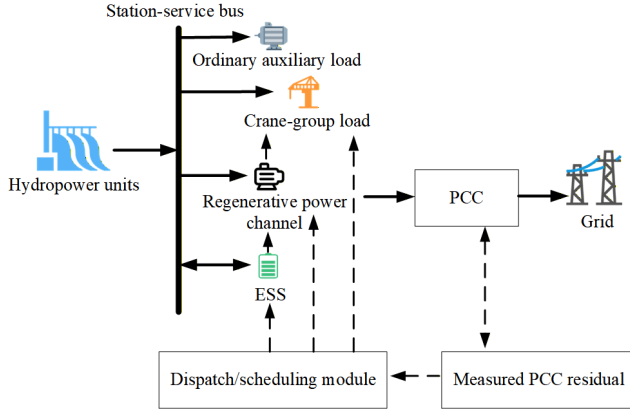


Figure 1. PCC-coupled electrical boundary of hydropower-station crane-group station-service loads

coincide with remaining local absorption capability. Figure 1 summarizes this PCC-coupled boundary.

2.2. Phase-resolved crane-task representation

The phase-resolved load block connects mechanical tasks with electrical impacts. A crane task consists of mechanically ordered phases, such as preparation, hoisting, traveling, lowering, braking, and standby. Empirical crane-energy studies show that these phases have different electrical roles: hoisting and acceleration create peak demand, whereas lowering and braking may create recoverable energy [4, 5]. Each task is represented as a movable block whose internal order is fixed.

Let $\mathcal{J}$ be the set of planned tasks, $\mathcal{K}_j$ the feasible mode set of task j , and $\tau_{j,k}$ the duration of mode k . Each mode has paired consumption and potential-regeneration templates,

$$\begin{cases} \mathbf{p}_{j,k} = (\mathbf{p}_{j,k}^c, \mathbf{p}_{j,k}^r) \\ \mathbf{p}_{j,k}^u = (p_{j,k,0}^u, p_{j,k,1}^u, \dots, p_{j,k,\tau_{j,k}-1}^u) \\ u \in \{c, r\} \end{cases} \quad (2)$$

In (2), the superscripts c and r denote active consumption and potential regeneration, respectively. The templates are uncertain before execution; Section 3 predicts them probabilistically. Once a task is started, the scheduling model preserves the internal phase order of the selected template.

If $x_{j,k,s}$ is one when task j starts at interval s under mode k , the aggregate crane consumption and potential regeneration are obtained by placing the task-relative templates on the absolute time axis:

$$\begin{cases} (p_t^{cg}, p_t^{rp}) = \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}_j} \sum_{s \in \mathcal{S}_{j,k}} \\ \sum_{\ell=0}^{\tau_{j,k}-1} (p_{j,k,\ell}^c, p_{j,k,\ell}^r) x_{j,k,s} \mathbb{I}(t = s + \ell) \end{cases} \quad (3)$$

Equation (3) maps each selected start time and mode onto a time-indexed power trajectory. Only the start time and admissible mode are decision variables; the internal phase order remains that of the mechanical task.

2.3. Safety-preserving load-block domain

The feasible start set and single-execution rule are defined before any electrical objective is introduced:

$$\begin{cases} \mathcal{S}_{j,k} = \{s \in \mathcal{T} : r_j \leq s, s + \tau_{j,k} - 1 \leq d_j\} \\ \sum_{k \in \mathcal{K}_j} \sum_{s \in \mathcal{S}_{j,k}} x_{j,k,s} = 1 \quad \forall j \in \mathcal{J}^M \end{cases} \quad (4)$$

In (4), r_j and d_j are the release time and deadline, and $\mathcal{J}^M$ denotes mandatory tasks. Optional tasks use the same window with a service variable on the right-hand side. A task can be shifted only if the whole physical block remains inside its admissible window.

For precedence and delay assessment, the realized start, completion, and execution-state variables are defined together:

$$\begin{cases} S_j = \sum_{k,s} s x_{j,k,s} \\ C_j = \sum_{k,s} (s + \tau_{j,k}) x_{j,k,s} \\ z_{j,t} = \sum_{k,s,\ell} x_{j,k,s} \mathbb{I}(t = s + \ell) \end{cases} \quad (5)$$

The start and completion times in (5) enter the precedence and delay constraints. The execution-state variable $z_{j,t}$ records whether task j occupies interval t and is used by the access, precedence, and occupation constraints.

The hydropower-specific flexibility domain consists of rigid-task fixation, a preferred-start window for semi-flexible tasks, access restrictions, precedence, and crane occupation:

$$\begin{cases} x_{j,k_j^0,s_j^0} = 1 & j \in \mathcal{J}^R \\ \bar{S}_j - L_j^- \leq S_j \leq \bar{S}_j + L_j^+ & j \in \mathcal{J}^S \\ z_{j,t} \leq A_{j,t} & j \in \mathcal{J}, t \in \mathcal{T} \\ C_i + \delta_{i,j} \leq S_j & (i, j) \in \mathcal{P} \\ \sum_{j,k,s,\ell} a_{j,k,c} x_{j,k,s} \mathbb{I}(t = s + \ell) \leq 1 \quad c \in \mathcal{C}, t \in \mathcal{T} \end{cases} \quad (6)$$

In (6), rigid tasks include emergency gate operations and safety-critical hoisting. Semi-flexible tasks remain near their preferred start. Access restrictions remove intervals prohibited by work permits, hydraulic conditions, unit tests, or site rules. Precedence and crane occupation complete the feasible domain.

2.4. Regenerative-energy interface and station-service coupling

The regenerative interface distinguishes energy that can be produced from energy that can be used. Potential regenerative power is created mechanically during lowering or braking. It is absorbed, stored, or fed through an enabled interface only when that interface has remaining capacity; otherwise it is curtailed or dissipated. The absorbed, stored, and curtailed portions are modeled as

$$\begin{cases} P_t^{\text{rp}} = P_t^{\text{ra}} + P_t^{\text{rE}} + P_t^{\text{rc}} \\ 0 \leq P_t^{\text{ra}} \leq \bar{P}_t^{\text{ra}} \\ 0 \leq P_t^{\text{rE}} \leq \bar{P}_t^{\text{rE}} \\ P_t^{\text{rc}} \geq 0 \end{cases} \quad (7)$$

The decomposition in (7) separates potential regenerative power from absorbed, stored, and curtailed recovery.

When an ESS is available, the storage state and net ESS power are

$$\begin{cases} E_{t+1} = E_t + \eta^{\text{ch}}(P_t^{\text{ch,g}} + P_t^{\text{rE}})\Delta t - \frac{P_t^{\text{dis}}}{\eta^{\text{dis}}}\Delta t \\ E^{\text{min}} \leq E_t \leq E^{\text{max}} \\ 0 \leq P_t^{\text{ch,g}} \leq \bar{P}^{\text{ch}} \\ 0 \leq P_t^{\text{dis}} \leq \bar{P}^{\text{dis}} \\ P_t^{\text{ESS}} = P_t^{\text{dis}} - P_t^{\text{ch,g}} \end{cases} \quad (8)$$

In (8), regenerative charging and grid-side charging are kept separate. Regenerative charging stores energy that would otherwise be curtailed, whereas grid-side charging increases the internal electrical burden.

Combining the electrical boundary, load-block mapping, safety domain, and regenerative interface yields the station-service burden used by the scheduler:

$$\begin{cases} P_t^{\text{ss}} = P_t^{\text{0,aux}} + P_t^{\text{cg}} + P_t^{\text{ch,g}} - P_t^{\text{dis}} - P_t^{\text{ra}} \\ P_t^{\text{PCC}} = P_t^{\text{unit}} - P_t^{\text{ss}} \end{cases} \quad (9)$$

In (9), the templates that enter P_t^{cg} and P_t^{rp} are predicted in Section 3. The admissible start times, modes, regenerative absorption, and ESS actions that shape P_t^{ss} and P_t^{PCC} are decided in Section 4.

3. Phase-aware probabilistic forecasting model

Phase-aware probabilistic forecasting represents future crane tasks as schedulable uncertain load blocks. Section 2 showed that task start time and execution mode affect the station-service power trajectory, but the actual trajectory is not fully known before execution. The same task type may still produce different feeder-power curves because of unobserved mechanical conditions and operator action. The scheduling model uses task-level probabilistic templates rather than a single aggregate station-service forecast.

Because crane-task timing itself is a scheduling variable, the forecasting model generates relative consumption and regeneration templates indexed by internal task phase positions, rather than a station-service curve at a fixed clock time. The optimization model then moves load blocks while preserving the physical task sequence.

3.1. Forecasting target and aligned data structure

For each historical or planned task, the model constructs a feature vector $\xi_{j,k,\ell} = [\xi_j^{\text{task}}, \xi_{j,k}^{\text{mode}}, \xi_{j,k,\ell}^{\text{phase}}, \xi_{t(j,\ell)}^{\text{elec}}, \xi_{j,k,\ell}^{\text{hist}}]$ that combines task, mode, phase, electrical-context, and recent-history descriptors. Task descriptors explain the mechanical work; mode descriptors explain the selected execution procedure; phase descriptors preserve the internal sequence; electrical-context descriptors capture station-service and unit states; recent-history descriptors capture thermal, utilization, and operator-state effects. The inputs used here are task and work-order descriptors, station-service and AGC/PCC context, crane feeder power at 1 s, and drive or PLC status words.

The signed crane feeder power is separated into positive consumption and potential regeneration:

$$\begin{cases} y_{j,k,\ell}^{\text{c}} = \max(p_{i(j,k),t(j,\ell)}^{\text{m}}, 0) \\ y_{j,k,\ell}^{\text{r}} = \max(-p_{i(j,k),t(j,\ell)}^{\text{m}}, 0) \end{cases} \quad (10)$$

Averaging the two parts of (10) into a net value would cancel the peak and the regenerative interval that enter PCC tracking and regenerative-energy scheduling. A high positive peak and a regenerative interval remain distinct even if their task-level energy nearly cancels.

The forecasting target is a pair of conditional distributions and their quantile representation:

$$\begin{cases} F_{j,k,\ell}^u(p) = \Pr(y_{j,k,\ell}^u \leq p \mid \xi_{j,k,\ell}) \\ \hat{q}_{j,k,\ell}^{u,\beta} = (F_{j,k,\ell}^u)^{-1}(\beta) \\ u \in \{\text{c}, \text{r}\} \end{cases} \quad (11)$$

In (11), the median quantile provides the nominal template, upper consumption quantiles describe peak

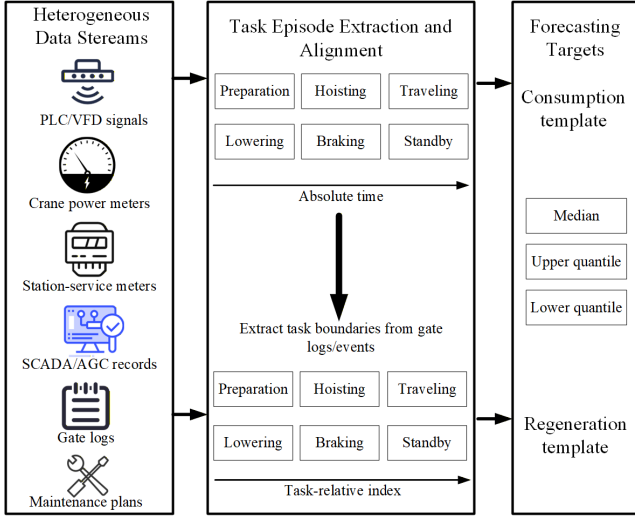


Figure 2. Data alignment and task-relative forecasting target

risk, and lower regeneration quantiles describe conservative recoverable power. Underestimating consumption and overestimating regeneration produce different residuals in the subsequent schedule. Figure 2 illustrates the task-relative data alignment and forecasting target.

3.2. Physics-constrained phase recognition

Crane peaks and regenerative intervals are phase-dependent. Phase labels are not stored as an independent channel: the drive and PLC records provide current, speed and status words, while the work-order system provides task names with start and stop events. A physics-constrained phase recognizer is applied before template learning. Let $s_{i,t}$ be the phase of crane i , selected from preparation, hoisting, traveling, lowering, braking, standby, and off states. Using the observation vector $\mathbf{o}_{i,t}$ assembled from drive or PLC words—hoist speed, traveling speed, VFD current, DC-bus voltage and interlock status—together with crane feeder power and the gate-log state when a gate task is active, the phase sequence is estimated by

$$\begin{cases} \hat{\mathbf{s}}_{i,1:N} = \arg \max_{\mathbf{s}_{i,1:N}} \left[\sum_{t=1}^N \log b_{s_{i,t}}(\mathbf{o}_{i,t}) \right. \\ \quad \left. + \sum_{t=2}^N \log a_{s_{i,t-1}, s_{i,t}} + \sum_u \log h_{s_u}(d_u) \right] \\ a_{r,s} = 0 \quad \text{if } (r, s) \notin \mathcal{A}^{\text{ph}} \end{cases} \quad (12)$$

In (12), the semi-Markov duration term prevents mechanically implausible rapid switching among phases, while the admissible transition set removes impossible phase changes. Crane phases have physical persistence, which the duration term and admissible transitions encode.

Recognized phases also define the regeneration mask used by the forecasting and scheduling layers:

$$\begin{cases} M_{j,k,\ell}^c = \mathbb{I}(\hat{s}_{j,k,\ell} \notin \{\text{off}\}) \\ M_{j,k,\ell}^r = \mathbb{I}(\hat{s}_{j,k,\ell} \in \{\text{lowering, braking}\}) \\ \mathcal{D}_e = \{\xi_{e,\ell}, \hat{s}_{e,\ell}, y_{e,\ell}^c, y_{e,\ell}^r\}_{\ell=0}^{\tau_e-1} \end{cases} \quad (13)$$

The masks in (13) connect the recognized physical phase to the probabilistic model. M^c suppresses off-state consumption, while M^r prevents random negative meter noise or local measurement errors from being interpreted as physically recoverable energy. The extracted sample set $\mathcal{D}_e$ is then used both for quantile-template learning and for scenario construction.

3.3. Phase-conditioned quantile template learning

The forecasting model is a phase-conditioned heteroscedastic quantile model. It is heteroscedastic because a heavy lift, a gate operation under uncertain hydraulic resistance, and a routine material transfer do not have the same uncertainty scale. Industrial probabilistic-load-forecasting studies use predictive distributions when load volatility and input-dependent uncertainty are strong [23]. Following the quantile-regression principle [30], the shared representation and monotone quantile heads are

$$\begin{cases} \mathbf{h}_{j,k,\ell} = \Psi_{\theta}(\xi_{j,k,\ell}, \hat{s}_{j,k,\ell}, \ell/\tau_{j,k}) \\ \hat{q}_{j,k,\ell}^{u,\beta_b} = M_{j,k,\ell}^u \left[\hat{q}_{j,k,\ell}^{u,\beta_{b-1}} + \text{softplus}(a_b^u(\mathbf{h}_{j,k,\ell})) \right] \\ \hat{q}_{j,k,\ell}^{u,\beta_0} = 0 \quad u \in \{c, r\}, b = 1, \dots, B \end{cases} \quad (14)$$

The cumulative positive increment in (14) prevents quantile crossing and enforces non-negativity, while the masks in (13) keep the predicted consumption and regeneration compatible with the recognized phase.

The model is trained using a quantile loss with weak smoothness and energy-consistency regularization:

$$\begin{cases} \mathcal{L}_Q = \sum_{e,\ell,b,u} \rho_{\beta_b}(y_{e,\ell}^u - \hat{q}_{e,\ell}^{u,\beta_b}) + \lambda_{\text{sm}} \mathcal{R}_{\text{sm}} + \lambda_E \mathcal{R}_E \\ \rho_{\beta}(v) = v(\beta - \mathbb{I}(v < 0)) \end{cases} \quad (15)$$

The smoothness regularizer in (15) suppresses sensor-induced oscillations in the median template, while the energy-consistency term prevents the high-resolution predicted template from drifting away from the task energy implied by the feeder-power integral.

When the duration of a phase is uncertain, the same quantile-learning idea is applied to duration. Conservative high-duration quantiles are used for safety-critical tasks, and scenario duration sampling is used for long maintenance windows.

3.4. Dependence-preserving scenarios and calibration

Pointwise quantiles quantify marginal uncertainty, but the scheduler also needs temporally coherent scenarios. Independent sampling at each internal index would destroy the relationship between phase duration, power amplitude and regeneration. Standardized residual trajectories from physically similar historical tasks are resampled instead, and each scenario is weighted by descriptor similarity:

$$\begin{cases} \varepsilon_{e,\ell}^u = \frac{y_{e,\ell}^u - \hat{q}_{e,\ell}^{u,0.5}}{\hat{q}_{e,\ell}^{u,0.9} - \hat{q}_{e,\ell}^{u,0.1} + \epsilon} \\ \tilde{p}_{j,k,\ell}^{u,\omega} = M_{j,k,\ell}^u [\hat{q}_{j,k,\ell}^{u,0.5} + \varepsilon_{e,\ell}^u (\hat{q}_{j,k,\ell}^{u,0.9} - \hat{q}_{j,k,\ell}^{u,0.1} + \epsilon)]_+ \\ \pi_\omega = \frac{\exp(-\|\eta_{j,k} - \eta_{e_\omega}\|_2^2 / \sigma_\eta^2)}{\sum_{e \in \mathcal{N}_{j,k}} \exp(-\|\eta_{j,k} - \eta_e\|_2^2 / \sigma_\eta^2)} \end{cases} \quad (16)$$

In (16), the selected historical episode e_ω is drawn from neighbors with similar crane type, work-order task type, recognized phase sequence, and phase-duration class. The descriptor vector η contains these historical descriptors and is distinct from the execution-state variable $z_{j,t}$. Each scenario preserves the marginal uncertainty and the temporal shape of a physically plausible crane-task trajectory.

To improve coverage reliability, the quantile intervals are calibrated by conformalized quantile regression [31]:

$$\mathcal{I}_{n,1-\alpha}^{\text{cal}} = [\hat{q}^{\alpha/2}(\xi_n) - \delta_{\alpha,\hat{s}_n}, \hat{q}^{1-\alpha/2}(\xi_n) + \delta_{\alpha,\hat{s}_n}] \quad (17)$$

The phase-dependent adjustment $\delta_{\alpha,\hat{s}_n}$ in (17) is obtained from calibration residuals within the same recognized phase. This prevents a calm standby phase and a high-risk hoisting phase from sharing the same uncertainty correction.

The forecasting layer is evaluated using pinball loss, empirical interval coverage, average interval width, and task-level peak recall, following the probabilistic-forecast evaluation logic of sharpness and calibration [32].

3.5. Scheduling interface and rolling update

The forecasting output passed to Section 4 comprises the median template, the calibrated interval, and the scenario set:

$$\begin{cases} \tilde{p}_{j,k,\ell}^u = \hat{q}_{j,k,\ell}^{u,0.5} \\ [p_{j,k,\ell}^u, \bar{p}_{j,k,\ell}^u] = \mathcal{I}_{(j,k,\ell,u),1-\alpha}^{\text{cal}}, \quad u \in \{c, r\} \\ \Phi_{j,k} = \left\{ \tilde{p}_{j,k,\ell}^u, p_{j,k,\ell}^u, \bar{p}_{j,k,\ell}^u, \tilde{p}_{j,k,\ell}^{\omega}, \pi_\omega : \right. \\ \left. u \in \{c, r\}, 0 \leq \ell < \tau_{j,k}, \omega \in \Omega_{j,k} \right\} \end{cases} \quad (18)$$

In (18), the median supports expected-cost scheduling, the interval supports conservative scheduling, and the scenarios support stochastic scheduling. A task-mode peak-risk indicator is also passed to the scheduler. Equation (19) is the probability that a task-mode pair creates an excessive short-time consumption peak:

$$R_{j,k}^{\text{pk}}(\bar{P}) = \sum_{\omega \in \Omega_{j,k}} \pi_\omega \mathbb{I} \left(\max_{0 \leq \ell < \tau_{j,k}} \tilde{p}_{j,k,\ell}^{c,\omega} \geq \bar{P} \right) \quad (19)$$

At each commitment epoch the quantile heads are re-evaluated on the latest crane status, phase labels, and power samples in $\mathcal{H}_\tau$.

4. Low-carbon rolling demand-response scheduling model

The rolling demand response model converts probabilistic task templates into executable station-service-side schedules. It selects admissible task start times and execution modes and coordinates regenerative-energy absorption and optional ESS actions.

The model adopts rolling mixed-integer programming. At each step, only the near-term open-loop decision is implemented. The problem is reconstructed when new work orders, crane states, PCC residuals or forecast templates become available. Crane tasks remain subject to operator approval, safety authorization and changing maintenance progress.

4.1. Rolling horizon and forecast-embedded aggregation

At decision epoch r , the optimization horizon is $\mathcal{T}_r = \{r, r+1, \dots, r+H-1\}$. Completed task phases are fixed, non-interruptible ongoing phases are committed, and only the remaining task blocks are optimized. The scenario-dependent crane consumption and potential regeneration are generated by embedding the Section 3 templates into the rolling horizon:

$$\begin{aligned} (P_t^{\text{cg},\omega}, P_t^{\text{rp},\omega}) &= (P_t^{\text{cg},\text{fix},\omega}, P_t^{\text{rp},\text{fix},\omega}) + \sum_{j \in \mathcal{J}_t^u} \sum_{k \in \mathcal{K}_j} \\ &\sum_{s \in \mathcal{W}_{j,k,r}} \sum_{\ell=0}^{\tau_{j,k}-1} (\tilde{p}_{j,k,\ell}^{c,\omega}, \tilde{p}_{j,k,\ell}^{r,\omega}) x_{j,k,s} \mathbb{I}(t = s + \ell) \end{aligned} \quad (20)$$

Equation (20) is the scheduling counterpart of (3). The fixed terms represent ongoing or already authorized work, while the summation covers unstated tasks whose flexibility is still available. If a robust deterministic schedule is required, the scenario templates are replaced by upper consumption and lower regeneration bounds.

4.2. Safety-preserving task scheduling constraints

The task scheduling domain in Section 2 is specialized to the rolling horizon. An unstarted task is assigned through a service indicator: mandatory tasks have $\chi_j = 1$, optional tasks have $\chi_j = y_j$, and rigid tasks are fixed.

$$\begin{cases} \sum_{k \in \mathcal{K}_j} \sum_{s \in \mathcal{W}_{j,k,r}} x_{j,k,s} = \chi_j \\ \chi_j = \begin{cases} 1, & j \in \mathcal{J}_r^M, \\ y_j, & j \in \mathcal{J}_r^O \end{cases} \\ x_{j,k_j^0,s_j^0} = 1 \quad j \in \mathcal{J}_r^R \end{cases} \quad (21)$$

In (21), $\mathcal{J}_r^M$ denotes mandatory tasks, $\mathcal{J}_r^O$ denotes optional or deferrable tasks, and $\mathcal{J}_r^R$ denotes rigid tasks. The service variable y_j allows a flexible task whose deadline lies outside the current horizon to be postponed to later rolling optimization.

Execution state, access windows, precedence, crane occupation, and shared-resource limits are

$$\begin{cases} z_{j,t} = \sum_{k,s,\ell} x_{j,k,s} \mathbb{I}(t = s + \ell) \\ z_{j,t} \leq A_{j,t} \\ C_i + \delta_{i,j} \leq S_j + M^{\text{pr}}(2 - \chi_i - \chi_j) \\ \sum_{j,k,s,\ell} a_{j,k,c} x_{j,k,s} \mathbb{I}(t = s + \ell) \leq 1 \\ \sum_{j,k,s,\ell} b_{j,k,g} x_{j,k,s} \mathbb{I}(t = s + \ell) \leq \bar{B}_{g,t} \\ (i, j) \in \mathcal{P}, \quad c \in \mathcal{C}, \quad g \in \mathcal{G} \end{cases} \quad (22)$$

A task occupies only permitted intervals in (22). Precedence is enforced when both tasks are selected, using χ_j from (21). Cranes, crews, and work zones cannot exceed their capacities.

4.3. Regenerative-energy and ESS constraints

The potential regenerative power produced by the scheduled task phases is separated into direct absorption, ESS storage, and curtailment:

$$\begin{cases} P_t^{\text{rp},\omega} = P_t^{\text{ra},\omega} + P_t^{\text{re},\omega} + P_t^{\text{rc},\omega} \\ 0 \leq P_t^{\text{ra},\omega} \leq \min\{\bar{P}_t^{\text{ra}}, P_t^{0,\text{aux}} + P_t^{\text{cg},\omega}\} \\ 0 \leq P_t^{\text{re},\omega} \leq \bar{P}_t^{\text{re}} \end{cases} \quad (23)$$

Direct absorption in (23) is limited by converter capability and by simultaneous local demand. Regenerative storage is limited by ESS charging capability, and the remaining part is curtailed.

The ESS dynamics and bounds are written as

$$\begin{cases} E_{t+1}^\omega = E_t^\omega + \eta^{\text{ch}}(P_t^{\text{ch},g,\omega} + P_t^{\text{re},\omega})\Delta t \\ \quad - \frac{P_t^{\text{dis},\omega}}{\eta^{\text{dis}}}\Delta t \\ E^{\min} \leq E_t^\omega \leq E^{\max} \quad E_r^\omega = E_r \\ 0 \leq P_t^{\text{ch},g,\omega} \leq \bar{P}^{\text{ch}} u_t^{\text{ch},\omega} \\ 0 \leq P_t^{\text{dis},\omega} \leq \bar{P}^{\text{dis}} u_t^{\text{dis},\omega} \\ u_t^{\text{ch},\omega} + u_t^{\text{dis},\omega} \leq 1 \end{cases} \quad (24)$$

In (24), grid-side charging and regenerative charging remain separate for the same reason explained in Section 2. Regenerative charging uses energy that would otherwise be dissipated, whereas grid-side charging increases the station-service burden.

4.4. Station-service and PCC constraints

The scheduled crane tasks, ESS action, and directly absorbed regeneration determine the scenario-dependent station-service load and PCC power:

$$\begin{cases} P_t^{\text{ss},\omega} = P_t^{0,\text{aux}} + P_t^{\text{cg},\omega} + P_t^{\text{ch},g,\omega} - P_t^{\text{dis},\omega} - P_t^{\text{ra},\omega} \\ P_t^{\text{PCC},\omega} = P_t^{0,\text{unit}} + \Delta P_t^{\text{unit}} - P_t^{\text{ss},\omega} \end{cases} \quad (25)$$

The compensation variable ΔP_t^{unit} in (25) is optional. If the crane scheduler is not allowed to coordinate with unit dispatch, it is fixed to zero. If limited coordination is allowed, unit-side compensation is restricted by AGC residual and ramp margins, and the PCC tracking and ramping residuals are linearized:

$$\begin{cases} -\bar{R}_t^{\text{down}} \leq \Delta P_t^{\text{unit}} \leq \bar{R}_t^{\text{up}} \\ -\bar{\rho}_t^{\text{unit}} \leq \Delta P_t^{\text{unit}} - \Delta P_{t-1}^{\text{unit}} \leq \bar{\rho}_t^{\text{unit}} \\ P_t^{\text{PCC},\omega} - P_t^{\text{ref}} = e_t^{+,\omega} - e_t^{-,\omega} \\ (P_t^{\text{PCC},\omega} - P_{t-1}^{\text{PCC},\omega}) - \Delta P_t^{\text{ref}} = r_t^{+,\omega} - r_t^{-,\omega} \\ e_t^{+,\omega}, e_t^{-,\omega}, r_t^{+,\omega}, r_t^{-,\omega} \geq 0 \end{cases} \quad (26)$$

In (26), $\Delta P_t^{\text{ref}} = P_t^{\text{ref}} - P_{t-1}^{\text{ref}}$. Unit-side compensation is limited by the AGC residual and ramp margins above. The residual variables enter the grid-friendliness term.

The station-service peak and the transformer capacity limit are represented by

$$\begin{cases} p^{\text{pk}} \geq P_t^{\text{ss},\omega} \\ P_t^{\text{ss},\omega} \leq \bar{P}_t^{\text{ss}} + h_t^{\text{ss},\omega} \\ h_t^{\text{ss},\omega} \geq 0 \end{cases} \quad (27)$$

The slack $h_t^{\text{ss},\omega}$ in (27) is heavily penalized and is retained only to diagnose infeasibility under rigid tasks and forecast uncertainty. In feasible operation its optimized value is zero.

4.5. Low-carbon and grid-friendly objective function

The objective function aggregates the grid, carbon, regeneration, task, peak, and risk terms:

$$\min J = \mathbb{E}_\omega \left[J^{\text{grid},\omega} + J^{\text{carb},\omega} + J^{\text{regen},\omega} \right] + J^{\text{task}} + J^{\text{pk}} + J^{\text{risk}} \quad (28)$$

The expected terms in (28) capture scenario-dependent electrical and low-carbon consequences, while task, peak, and risk terms are shared across the rolling horizon.

The grid-friendliness term (29) penalizes PCC tracking residuals, ramping residuals, and station-service capacity slack:

$$J^{\text{grid},\omega} = \sum_{t \in T_r} \left[\lambda_e (e_t^{+, \omega} + e_t^{-, \omega}) + \lambda_p (r_t^{+, \omega} + r_t^{-, \omega}) + \lambda_h h_t^{\text{ss}, \omega} \right] \quad (29)$$

The low-carbon and regenerative-energy terms (30) are

$$\begin{cases} J^{\text{carb},\omega} + J^{\text{regen},\omega} = \lambda_c \sum_{t \in T_r} \gamma_t P_t^{\text{ctrl},\omega} \Delta t \\ \quad + \lambda_{\text{rc}} \sum_{t \in T_r} P_t^{\text{rc},\omega} \Delta t \\ P_t^{\text{ctrl},\omega} \geq P_t^{\text{cg},\omega} + P_t^{\text{ch},\omega} - P_t^{\text{dis},\omega} - P_t^{\text{ra},\omega} \\ P_t^{\text{ctrl},\omega} \geq 0 \end{cases} \quad (30)$$

The coefficient γ_t is the time-varying carbon-opportunity signal. It is dimensionless and normalized to unit mean over the horizon; Section 4.6 gives its definition and construction. The controllable station-service burden excludes ordinary station-service load because the scheduling model does not control it, and the non-negativity condition prevents regeneration or ESS discharge from creating an artificial negative carbon cost. The curtailment term gives an explicit penalty to wasting physically available regenerative energy.

Task-disruption and peak costs (31) are

$$\begin{cases} J^{\text{task}} + J^{\text{pk}} = \sum_{j \in \mathcal{J}_r^S \cup \mathcal{J}_r^F} (\lambda_j^+ d_j^+ + \lambda_j^- d_j^- + \lambda_j^{\text{miss}} (1 - \chi_j)) \\ \quad + \lambda_{\text{pk}} P^{\text{pk}} \\ d_j^+ \geq S_j - \bar{S}_j - M^d (1 - \chi_j) \\ d_j^- \geq \bar{S}_j - S_j - M^d (1 - \chi_j) \\ d_j^+, d_j^- \geq 0 \end{cases} \quad (31)$$

The delay and anticipation penalties are activated only when the task is selected, while the missed-service penalty applies when an optional task is

postponed outside the current rolling horizon. Different anticipation and delay weights are allowed because advancing and postponing a task have different work-order consequences.

A CVaR term (32) is included for the tail of the scenario loss:

$$\begin{cases} J^{\text{risk}} = \lambda_{\text{CVaR}} \left[\nu + \frac{1}{1 - \beta} \sum_{\omega \in \Omega} \pi_\omega \zeta_\omega \right] \\ \zeta_\omega \geq L_\omega - \nu \\ \zeta_\omega \geq 0 \\ L_\omega = \sum_{t \in T_r} \left[\lambda_e (e_t^{+, \omega} + e_t^{-, \omega}) + \lambda_p (r_t^{+, \omega} + r_t^{-, \omega}) + \lambda_h h_t^{\text{ss}, \omega} \right] \end{cases} \quad (32)$$

The adverse-loss variable L_ω is the PCC tracking, ramping, and station-service slack under scenario ω .

Combining the preceding components gives the rolling scheduling problem (33):

$$\begin{aligned} \mathbf{P}_r^* : \quad & \min_{\substack{\mathbf{x}, \mathbf{y}, \\ \mathbf{z}, \mathbf{u}, \\ \mathbf{E}, \mathbf{P}, \\ \mathbf{e}, \mathbf{r}, \\ \mathbf{d}, \mathbf{h}, \\ \zeta, \nu}} J \\ \text{s.t.} \quad & \text{aggregation (20)} \\ & \text{task and safety constraints (21)–(22)} \\ & \text{regeneration and ESS constraints (23)–(24)} \\ & \text{station-service and PCC constraints (25)–(27)} \\ & \text{objective auxiliaries (29)–(32)} \\ & x_{j,k,s}, y_j, z_{j,t} \in \{0, 1\} \\ & u_t^{\text{ch},\omega}, u_t^{\text{dis},\omega} \in \{0, 1\} \end{aligned} \quad (33)$$

Because (29)–(32) use absolute PCC and ramp deviations, a linear CVaR reformulation, and piecewise-linear task and peak penalties, the rolling problem in (33) is a mixed-integer linear program.

4.6. Construction of the carbon-opportunity coefficient

The coefficient γ_t represents an opportunity rather than an attributed emission. Station-service energy at a hydropower plant is supplied by the units themselves, so consuming one additional megawatt-hour internally at time t emits no carbon at the plant; it withholds one megawatt-hour of low-carbon export that would otherwise have displaced whatever generation sets the margin of the external system at that time. Writing μ_t for that marginal emission factor in tCO₂/MWh, the carbon-opportunity cost of a schedule over the rolling horizon is

$$C_r = \sum_{t \in T_r} \mu_t P_t^{\text{ctrl}} \Delta t \quad (34)$$

Equation (34) is the marginal-emission-factor formulation used in low-carbon demand response [27–29], applied to a withheld export rather than to a consumed import.

The absolute level of μ is not identifiable from a scheduling problem. Replacing μ_t by $c\mu_t$ for any $c > 0$ and λ_c by λ_c/c leaves the objective and hence the optimal schedule unchanged, so only the temporal shape of μ can alter a decision. The signal is normalized by its own horizon mean. Its shape is generated by a monotone map from a system-stress profile:

$$\begin{cases} \gamma_t = \frac{\mu_t}{\bar{\mu}}, & \bar{\mu} = \frac{1}{|T_r|} \sum_{\tau \in T_r} \mu_\tau \\ \mu_t = \mu_{lo} [1 + (\kappa - 1)\varphi_t], & \kappa = \frac{\mu_{hi}}{\mu_{lo}} \\ \gamma_t = \frac{1 + (\kappa - 1)\varphi_t}{1 + (\kappa - 1)\bar{\varphi}}, & \varphi_t \in [0, 1] \end{cases} \quad (35)$$

In (35), φ_t is a min–max normalized diurnal profile of external-system stress with horizon mean $\bar{\varphi}$, and μ_{lo} and μ_{hi} are the emission factors of the cleanest and the dirtiest technology that can set the margin. Two properties follow. First, γ_t is dimensionless and has mean exactly 1.0 by construction, so the reported carbon-opportunity cost is expressed in p.u. MWh. Second, μ_{lo} and μ_{hi} enter only through their ratio κ , because the common factor cancels in the normalization. The construction is fully specified by two inputs: the shape φ_t and the spread κ .

The stress profile φ_t follows the diurnal shape of regional net load, low overnight and around midday and high through the evening ramp, with $\bar{\varphi} = 0.50$ over the day. The spread is set to $\kappa = 2.45$, corresponding to a margin that moves between gas-fired and coal-fired units between the two ends of the day. Substituting these two values into (35) returns a signal of mean 1.0 spanning $\gamma_t \in [0.58, 1.42]$, which is the interval used in the case-study parameter table of Section 5. A published regional marginal emission factor or locational marginal emission rate can be substituted for μ_t in (34) without changing the rest of the formulation. Section 5.7 examines the sensitivity of the schedule to the amplitude of this signal.

4.7. Rolling implementation and computational treatment

The rolling implementation updates the problem at each epoch. Completed phases are fixed, non-interruptible ongoing phases are protected, newly issued tasks are inserted, and probabilistic templates are updated from the latest observations. The scheduler

Algorithm 1. Rolling low-carbon demand-response scheduling of hydropower crane groups

Inputs: initial task plan; crane availability; safety admission matrix A ; SCADA/AGC trajectory; ordinary auxiliary-load forecast; carbon-opportunity signal γ ; ESS state; rolling horizon H .

For each decision instant r :

- Read current crane status, completed phases, PCC residual, ESS state, and new work orders.
- Classify tasks into rigid, semi-flexible, flexible, optional, running, and completed sets.
- Fix completed and noninterruptible running task segments.
- Generate or update phase-aware probabilistic templates.
- Construct feasible start sets $W_{j,k,r}$ according to deadlines, safety admission, crane occupation, crew availability, and gate-operation limits.
- Solve the rolling MILP or MIQP.
- Execute only the first interval or the operator-approved short commitment window.
- Send the updated task schedule, ESS commands, and regenerative-absorption commands to the station operation interface.
- Advance r and repeat until the horizon ends.

Outputs: rolling task schedule; ESS trajectory; regenerative-absorption plan; PCC tracking residual; station-service peak; low-carbon operating metrics.

then solves (33), implements only the first interval or a short operator-approved commitment window, and repeats the process at the next epoch. Algorithm 1 summarizes this rolling procedure.

Several computational reductions are applied before solving. Dominated execution modes are removed when they have a longer duration, a higher peak risk, and are not required by a stricter safety class. Start times that violate work-access rules or deterministic crane conflicts with rigid tasks are deleted from the feasible set. Tasks whose deadlines lie outside the current rolling horizon are represented through reservation penalties unless they are within their latest-start boundary. The reductions remove infeasible or dominated candidates; they do not enlarge the safety-feasible set.

The model also separates planning decisions from protection actions. Emergency gate operations, flood-control actions, and interlock-triggered crane movements are imposed as rigid tasks or external constraints. The optimizer may reorganize flexible maintenance and support tasks around them; it cannot delay or suppress them. Figure 3 summarizes the rolling optimization structure.

The rolling model co-schedules crane tasks, regenerative-energy absorption, ESS operation, and

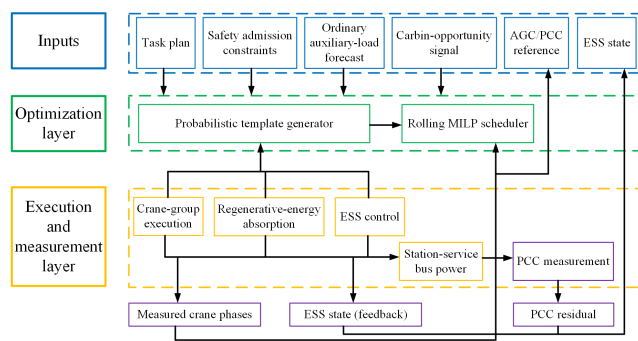


Figure 3. Rolling low-carbon optimization structure

PCC-oriented performance. Section 5 evaluates station-service peak control, PCC tracking, regenerative-energy utilization, carbon-opportunity cost, and task feasibility relative to the earliest-start baseline and deterministic counterparts.

5. Case study and results

Sections 2–4 have established the physical coupling, forecasting interface, and rolling scheduling model. This section examines whether these models can reduce station-service peaks, improve PCC tracking, increase regenerative-energy utilization, and reduce carbon-opportunity cost. To prevent the results section from becoming a parameter list, the case definition, numerical comparison, and mechanism explanation are placed in the same section. Each result subsection corresponds to a design choice in the forecast-to-dispatch framework.

The case parameters are set according to the operating logic of hydropower-station crane groups and the characteristics of station-service loads. They simulate typical situations in which crane peak loads overlap with ordinary station-service peaks, safety-rigid tasks are constrained by gate operation and personnel safety, regenerative phases are affected by local absorption capability, and crane-group consumption causes PCC net-power deviations during AGC-sensitive intervals. The case also verifies the applicability of the proposed model in the use of forecasting information, flexible task arrangement, regenerative-energy absorption, and station-level power coordination. Section 5.9 then presents an actual-station replay test using real-time data, so that the performance of the proposed method can be checked on the 15.00 MW installed fleet.

5.1. Station-oriented hydropower case, operating scenarios, and benchmark cases

The test system is an equivalent large hydropower station with six generating units, each rated at 700 MW. The installed capacity is therefore 4.2 GW, which

keeps gross generation much larger than the station-service load while allowing several megawatts of crane-group demand to influence short-time PCC tracking. The scheduling horizon is one operating day with a resolution of 15 min, giving $T = 96$ intervals. The unit-output trajectory is treated as an exogenous AGC-following path; the decision variables are station-service-side rather than hydraulic unit commitment. Ordinary station-service load, excluding crane groups, varies from 9.6 to 16.8 MW owing to cooling-water pumps, oil-pressure equipment, drainage pumps, air compressors, ventilation equipment, and temporary maintenance power supply. The station-service hard limit of 28 MW follows the rating of the station-service transformers. The soft peak reference of 22 MW is a scheduling parameter that penalizes auxiliary peaks before the security limit is approached. The ± 3 MW PCC tracking deadband is a study tolerance scaled to station-service disturbances: a 9.6–16.8 MW background load and individual crane tasks of up to about 2.35 MW.

The crane group contains six hoisting devices: two powerhouse bridge cranes, one dam-crest gantry crane, one intake gate hoist, one tailwater gantry crane, and one auxiliary maintenance hoist. They are modeled as shared operational resources rather than independent electrical devices, because a crane task may simultaneously occupy a crane, a unit bay, a gate slot, a crew, and a safety-access zone. The representative maintenance-intensive day contains 22 tasks, including 4 rigid tasks, 10 semi-flexible tasks, 6 flexible tasks, and 2 optional support tasks. Rigid tasks include emergency gate checks and lock-confirmation operations; semi-flexible tasks include scheduled gate inspection, trash-rack lifting, and unit-bay maintenance support; flexible tasks include material transfer and non-critical auxiliary hoisting. The peak consumption of a single task ranges from 0.35 to 2.35 MW, and the potential regenerative power ranges from 0.10 to 0.95 MW depending on the lowering and braking phases.

The fleet is mixed rather than uniform. It covers five of the device classes listed in Section 1.1 and sits at five physically distinct locations—powerhouse, dam crest, intake, tailwater and the mid-gate chamber of the spillway tunnel—which differ in travel distance, duty cycle, indoor or outdoor siting and safety regime. Single-task peaks span a factor of 6.7 and regenerative potential a factor of 9.5. This 10 MW digital case and the 15.00 MW actual-station archive in Section 5.9 are separate evaluations. Section 6 states the work-process conditions under which the same formulation can be instantiated.

A station-service ESS is included to distinguish electrical buffering from task-level demand response. The ESS has 2 MW rated power, 4 MWh rated

energy, and a round-trip efficiency of 0.90. It can absorb regenerative energy and discharge during local station-service peaks, but it cannot remove crane-task conflicts unless task placement is also optimized. A high value of the carbon-opportunity coefficient means that consuming internal hydropower at that time has a larger opportunity cost because exported hydropower would otherwise displace higher-carbon marginal generation. This coefficient is used as a scheduling signal rather than as a direct life-cycle carbon-emission factor, and the 0.58–1.42 p.u. entry in Table 1 is the output of Eq. (35) under the two inputs stated in Section 4.6. Table 1 summarizes the main case parameters.

Five scheduling cases are compared. Three instantiate published method classes on the same work orders; ES is the earliest-start baseline; and the remaining case, denoted Proposed, is the forecast-embedded rolling schedule. Table 2 states, for each case, the literature parent, what is transferred, and what is adapted to hydropower-station safety constraints and PCC tracking.

Initial scheduling (ES) executes each task as soon as its release time and safety constraints allow.

ESS-MPC instantiates the receding-horizon storage controllers developed for electrified crane networks [8–10]. Those studies keep the crane work sequence fixed and optimize only ESS charge, discharge and regenerative absorption. The same decision split is used here: the earliest-start task sequence is held fixed, and only the 2 MW/4 MWh buffer is dispatched. The original economic term is a time-of-use electricity cost, which is not how station-service energy is settled at a hydropower plant. It is replaced by station-service peak and PCC tracking residuals, the grid-facing quantities defined in Section 2. The rolling horizon is the 8 h / 15 min window already used by the station's 96-point daily dispatch schedule. With the crane sequence fixed, residual peak and tracking error remain.

PF-MILP instantiates load-block shifting [2, 25] and energy-aware crane-task MILP [16, 17]. Those formulations move an intact power block inside a feasible window but do not reshape the internal profile, and they do so with a deterministic or point-forecast description of that block. The same structure is used here: start times and modes of non-rigid tasks are optimized with median phase templates, subject to the release times, deadlines, precedence and occupation constraints. The market-clearing or quay-logistics objective is replaced by station-service peak and PCC residuals. PF-MILP is the literature load-block method under hydropower safety constraints.

GF-MILP instantiates carbon-blind, peak-oriented demand response [26–28]. That literature distinguishes reliability or peak-shaving DR from carbon-guided DR and requires the two to be reported separately, because

a schedule that improves tracking need not reduce carbon-opportunity cost. GF-MILP retains probabilistic templates, peak control, PCC tracking and regenerative coordination, and removes only the carbon-opportunity term. The difference between Proposed and GF-MILP is then that term.

Proposed uses phase-aware conformal templates, CVaR-type peak-risk treatment, regenerative-energy coordination, optional ESS recourse, and the low-carbon objective term.

Four ablation cases isolate components of Proposed. No-CVaR removes the probabilistic peak-risk term but keeps scenario-based expected costs. No-Regen-Co removes explicit coordination of regenerative phases, so regeneration is absorbed only opportunistically. No-Mode forbids alternative low-speed execution modes. No-Flex fixes all non-rigid tasks at their operator-preferred start times and allows only ESS dispatch. Figure 4 shows the study boundary and scheduling interface used for these comparisons.

5.2. Forecasting performance and its scheduling relevance

The forecasting comparison reports point-error and uncertainty metrics that later enter the scheduler: median templates, calibrated intervals, and peak-risk windows. Four models are compared: a history-only ARIMA model, a TCN point predictor with empirical residual intervals, a TFT-based quantile predictor, and the phase-aware conformal quantile model. ARIMA and TCN are the baselines for a conventional time-series model and a deep-learning point predictor, respectively. The TFT quantile model is a general probabilistic sequence model without explicit phase information. The phase-aware conformal model aligns the forecast target with the task-relative phase index and calibrates prediction intervals after phase-conditioned quantile learning. Table 3 reports the resulting 20-day metrics.

Table 3 shows that the phase-aware conformal model reduces MAPE by 14.4% relative to TFT-Quantile and by 29.7% relative to TCN. The 90% prediction interval coverage probability is 90.7%, close to the nominal level, while its mean prediction interval width is lower than that of the empirical TCN interval.

The phase-aware conformal model captures 85.9% of realized task peaks within the predicted high-risk intervals, compared with 78.6% for the TFT quantile model. A heavy powerhouse bridge-crane lift and a gate-hoist operation may occur at different clock times, but both contain a high-consumption hoisting phase followed by a lower-consumption or regenerative phase. Clock-time forecasting mixes those internal sequences; task-relative forecasting keeps the phase order, so the optimizer places high-consumption phases

Table 1. Main parameters of the station-oriented hydropower case

Item	Value	Source	Role
Installed hydropower capacity	6 × 700 MW	Plant rating	PCC evaluation boundary
Scheduling horizon	24 h	Study choice	Maintenance- and gate-operation day
Time resolution	15 min	Plant cycle	Decision grid; coincides with the 96-point daily dispatch schedule
Ordinary station-service load	9.6–16.8 MW	Study choice	Non-crane station-service load background
Station-service soft reference	22 MW	Study choice	Penalized avoidable auxiliary peak
Station-service hard limit	28 MW	Plant setting	Security constraint from the station-service transformer rating
PCC tracking deadband	±3 MW	Study choice	Tracking tolerance scaled to station-service disturbances
Crane-group aggregate rating	10 MW	Design envelope	Six devices, 0.5–2.5 MW each
Crane tasks in representative day	22	Study choice	Rigid, semi-flexible, flexible, and optional tasks
Individual task peak consumption	0.35–2.35 MW	Study choice	Crane power-template range
Potential regenerative power	0.10–0.95 MW	Study choice	Lowering/braking recovery range
ESS rating	2 MW/4 MWh	Auxiliary	Station-service buffer used in the comparison
Carbon-opportunity coefficient	0.58–1.42 p.u.	Auxiliary	Unit-mean signal; range from Eq. (35)
Rolling horizon	8 h	Study choice	Look-ahead window for task shifting
Forecast scenarios	30	Study choice	Uncertainty representation from historical residuals
CVaR confidence level	0.90	Study choice	Peak-risk scheduling level

Table 2. Literature parents of the scheduling cases and the adaptations used in the station-oriented case

Case	Literature parent	Transferred	Adapted to this station
ES	Field practice; ASAP convention in resource-constrained crane scheduling	Earliest feasible start under release and safety constraints	Operating baseline
ESS-MPC	Receding-horizon ESS control for electrified crane networks [8–10]	Crane sequence fixed; ESS is the only decision; rolling peak-oriented dispatch	Time-of-use cost replaced by station-service peak and PCC residual; 8 h / 15 min horizon; 2 MW/4 MWh buffer
PF-MILP	Load-block shifting and energy-aware crane-task MILP [2, 16, 25]	Intact load blocks shifted inside time windows by mixed-integer scheduling with a point forecast	Blocks are safety-classified crane tasks; power from phase-median templates; hydro safety and occupation constraints
GF-MILP	Carbon-blind peak / reliability DR [26–28]	Forecast-embedded scheduling for peak and tracking without a carbon signal	Same crane safety model; carbon-opportunity term removed
Proposed	Forecast-embedded rolling schedule	Phase-aware conformal templates, CVaR peak risk, regenerative coordination, optional ESS, carbon-opportunity term	Evaluated on the same work orders

rather than an aggregate load curve. Figure 5 gives the representative-day forecasting profiles used by the scheduling comparison.

5.3. Representative-day scheduling results and mechanism analysis

The representative day contains two distinct electrical conflicts. The interval from 09:45 to 11:45 is the overlap of rising ordinary station-service load with the

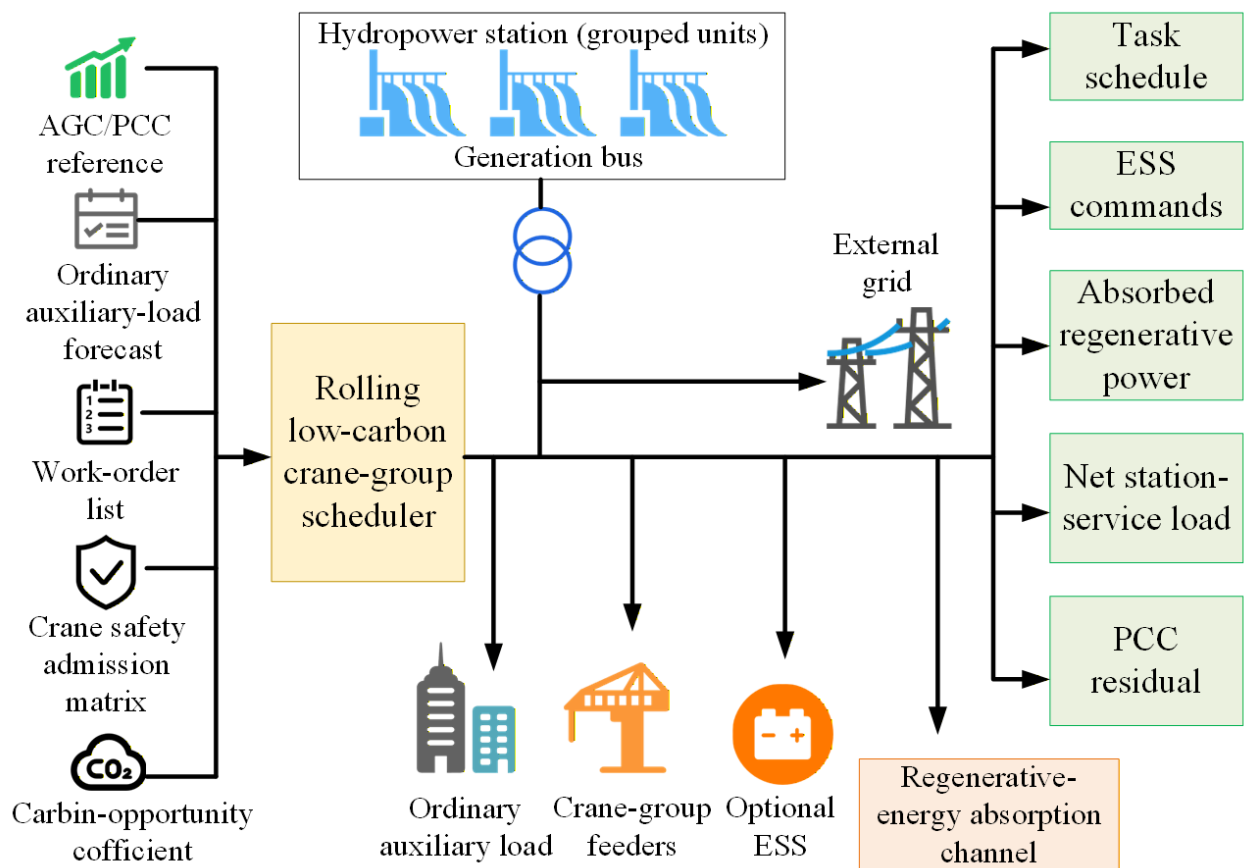


Figure 4. Station-oriented hydropower case and crane-group scheduling interface

Table 3. Forecasting performance over the 20 test days of the station-oriented case

Forecasting model	Main input structure	MAPE (%)	RMSE (MW)	Pinball loss	90% PICP (%)	MPIW (MW)	Peak-hit rate (%)
ARIMA	Historical aggregate crane load	16.9 ± 3.8	0.86 ± 0.14	–	77.4	1.12	61.7
TCN + empirical interval	Historical load and task count	11.8 ± 2.5	0.62 ± 0.10	0.088	82.9	0.95	72.4
TFT-Quantile	Multi-source task and system features	9.7 ± 2.0	0.51 ± 0.08	0.074	87.5	0.84	78.6
Proposed	Phase-conditioned task templates	8.3 ± 1.7	0.43 ± 0.07	0.061	90.7	0.78	85.9

release of several maintenance tasks, and is a station-service peak interval. The interval from 18:00 to 20:00 coincides with an upward-ramping PCC reference and a high carbon-opportunity coefficient, and is a PCC-tracking and carbon-timing interval.

Table 4 shows that Proposed reduces the station-service peak by 16.1% relative to ES and by 9.4% relative to ESS-MPC. Between ES and ESS-MPC, the ESS absorbs regenerative energy and discharges during peak intervals, reducing the station-service peak from

25.84 MW to 23.92 MW. Multiple high-power hoisting phases still occur in the same period. PF-MILP and GF-MILP further reduce the peak by moving semi-flexible and flexible tasks away from the morning station-service peak. On the representative day the station-service peak is determined by task timing; the ESS modifies absorption and smoothing only after those start times have been fixed.

Proposed uses forecast uncertainty rather than only the point-forecast load-block description transferred

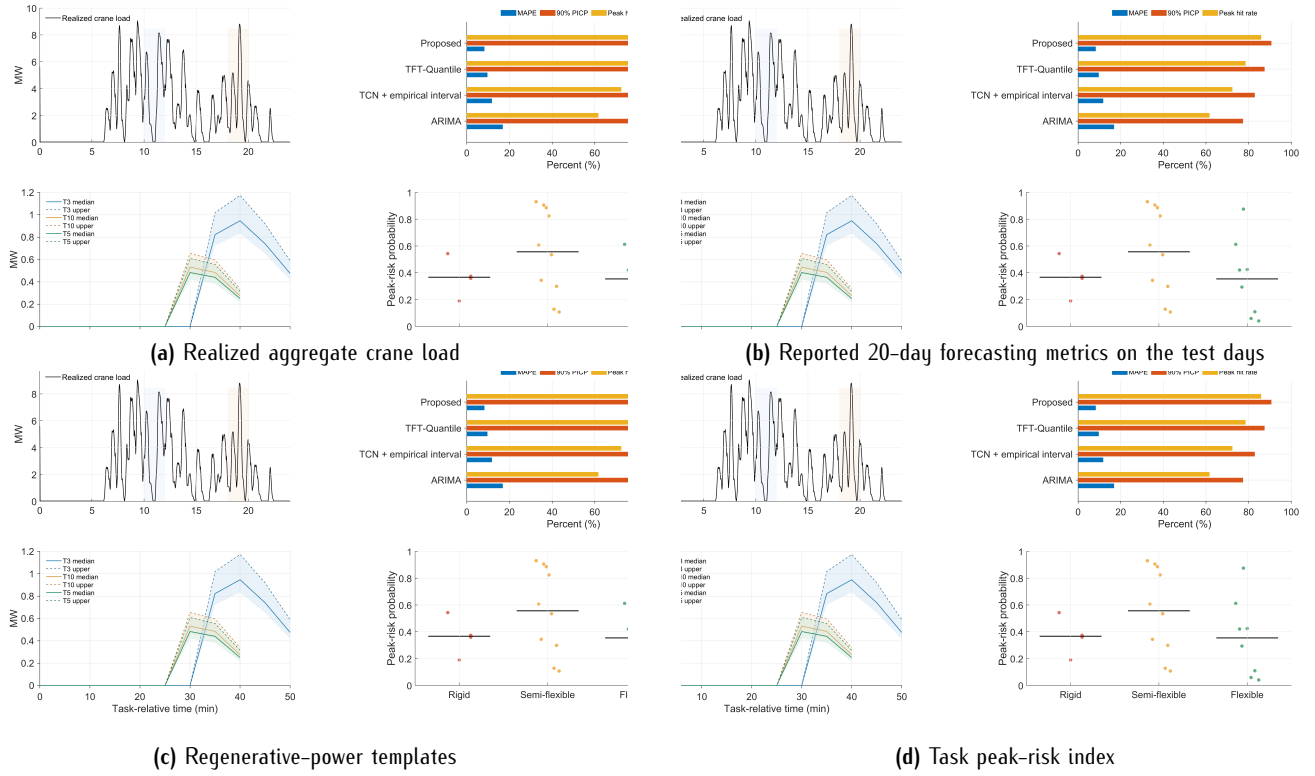


Figure 5. Forecasting results for the representative maintenance-intensive day

Table 4. Representative-day scheduling performance

Case	Station-service peak (MW)	95th-percentile station-service load (MW)	PCC RMSE (MW)	Max $ \Delta P_{PCC} $ (MW)	Regenerative utilization (%)	Carbon-opportunity cost (p.u. MWh)	Total task delay (h)	Deadline violations
ES	25.84	21.72	1.58	6.41	54.8	58.2	0.8	0
ESS-MPC	23.92	20.94	1.24	5.16	71.4	55.6	0.8	0
PF-MILP	22.58	20.36	0.95	3.74	79.5	48.1	5.6	0
GF-MILP	22.11	20.08	0.83	3.25	82.1	45.6	5.9	0
Proposed	21.67	19.74	0.71	2.95	86.8	40.9	6.4	0

from [2, 25]. On the representative day, two semi-flexible tasks have similar median power, but their phase-conditioned quantile widths differ because historical feeder-power residuals of those work-order types are not the same. PF-MILP places one of these tasks near the end of the morning peak; the realized power trajectory is higher than the predicted median, producing a short station-service excursion and a larger PCC residual. Proposed delays that task by 45 min and selects a lower-speed execution mode. Task duration and total delay increase; the station-level peak-risk residual decreases.

The total mechanical work of crane tasks is almost unchanged under ES, PF-MILP, GF-MILP, and Proposed because all tasks are still completed. Proposed reduces the carbon-opportunity cost by 29.7% relative to ES and by 10.3% relative to GF-MILP. High-consumption hoisting phases are placed in intervals with a lower carbon-opportunity coefficient, and high-carbon-opportunity intervals are left to rigid tasks or regenerative phases. The carbon-opportunity change is a timing change, not a change in physical energy consumption.

Regenerative-energy utilization increases from 54.8% under ES to 86.8% under Proposed. When the ESS

is close to its upper state-of-charge limit, overlapping regenerative phases are avoided. Some lowering and braking phases are placed in intervals with higher ordinary station-service consumption or remaining ESS absorption headroom. Regenerative power is scheduled subject to timing and absorption limits. The same limits account for the lower utilization of No-Regen-Co at the same ESS rating. Figure 6 shows the corresponding station-service and PCC residual trajectories.

5.4. From task shifting to phase shifting: detailed schedule interpretation

Task timings over the operating day differ across strategies. Under earliest-start scheduling, five semi-flexible or flexible tasks start within 90 min after their release times, which clusters several hoisting phases between 10:15 and 11:15. The station-service peak in this period comes from the superposition of several medium-power hoisting phases and the ordinary station-service peak, not from a limit violation of a single crane. Individual crane tasks remain in the sub-megawatt to several-megawatt range, yet the station-service peak under ES reaches 25.84 MW.

Proposed changes start times and modes according to task safety class, peak risk, and the station-level operating state. Four rigid tasks remain in the original schedule. Two flexible support tasks are advanced to early-morning intervals with a lower carbon-opportunity coefficient. Three semi-flexible maintenance tasks are delayed past the ordinary station-service peak, and two tasks are switched to low-speed mode. Advancement, delay, and mode switching are used together. High-consumption phases are distributed across the day; low-consumption preparation and positioning phases remain near the original maintenance sequence. The internal mechanical process of each task is unchanged.

Table 5 lists the scheduled start times and modes on the representative day. Rigid gate-related actions remain fixed by the rigid-task constraint. Flexible material transfer is moved to an interval with a lower carbon-opportunity coefficient. A semi-flexible bridge-crane support task is delayed and executed in low-speed mode because its hoisting-phase quantile width overlaps the morning peak. A tailwater gantry task is shifted outside the AGC upward-ramp interval, where an added crane peak would increase the PCC residual. Timing and mode changes are applied only to tasks that retain a nonempty flexibility set after safety, occupation, and precedence constraints are enforced.

Total delay is larger than under ES because ES starts almost every non-rigid task early. The added delay is confined to tasks that already have an explicit flexibility window and low process criticality. No rigid task is delayed, no deadline is violated, and

no precedence relationship is broken. The associated reductions are in station-service peak, PCC residual, regenerative curtailment, and carbon-opportunity cost. Delay penalties in the objective are weighted by work-order criticality rather than treated as uniform waiting costs. Figure 7 shows the same timing changes at the phase-load-block level.

5.5. Statistical comparison over 20 test days

The same indicators are reported over the 20 test days. Those days cover normal maintenance, maintenance-intensive, gate-operation-intensive, and mixed work-order patterns, with different ordinary station-service load curves, AGC references, task libraries, and realized forecast errors, together with the carbon-opportunity signal. The same forecasting model trained on historical tasks and the same scheduling parameters are used for all days.

Table 6 shows that across the 20 test days, Proposed reduces the average station-service peak by 16.8% relative to ES and by 10.1% relative to ESS-MPC. The standard deviation of the peak also decreases.

ESS-MPC reduces PCC RMSE by 21.9% relative to ES, PF-MILP by 39.7%, and Proposed by 54.3%. PCC error comes from instantaneous power imbalance and from the timing of crane peaks relative to AGC-sensitive periods. ESS control compensates part of the imbalance after it appears; it does not move the load block. Task scheduling changes the start time. Probabilistic scheduling further keeps high-risk tasks away from those intervals.

The carbon-opportunity cost decreases by 28.5% relative to ES, while average task delay increases from 2.1 to 17.2 minutes per task. Most of the added delay is assigned to flexible and semi-flexible tasks. No case violates a deadline. Among the compared feasible schedules, Proposed has the lowest station-service peak, PCC RMSE, and carbon-opportunity cost.

Task-level rescheduling without the ESS already reduces the average station-service peak to 22.6 MW and the PCC RMSE to 0.84 MW over the same 20 days (Section 5.7), that is by 11.7% and 44.4% relative to the earliest-start baseline. Adding the 2 MW/4 MWh buffer further lowers these figures to 16.8% and 54.3%, and carbon-opportunity cost falls by 22.9% without the buffer against 28.5% with it. Regenerative-energy utilization rises from 55.6% to 61.5% by task placement alone, and to 86.2% once the buffer is available to absorb pulses that do not coincide with ordinary station-service load.

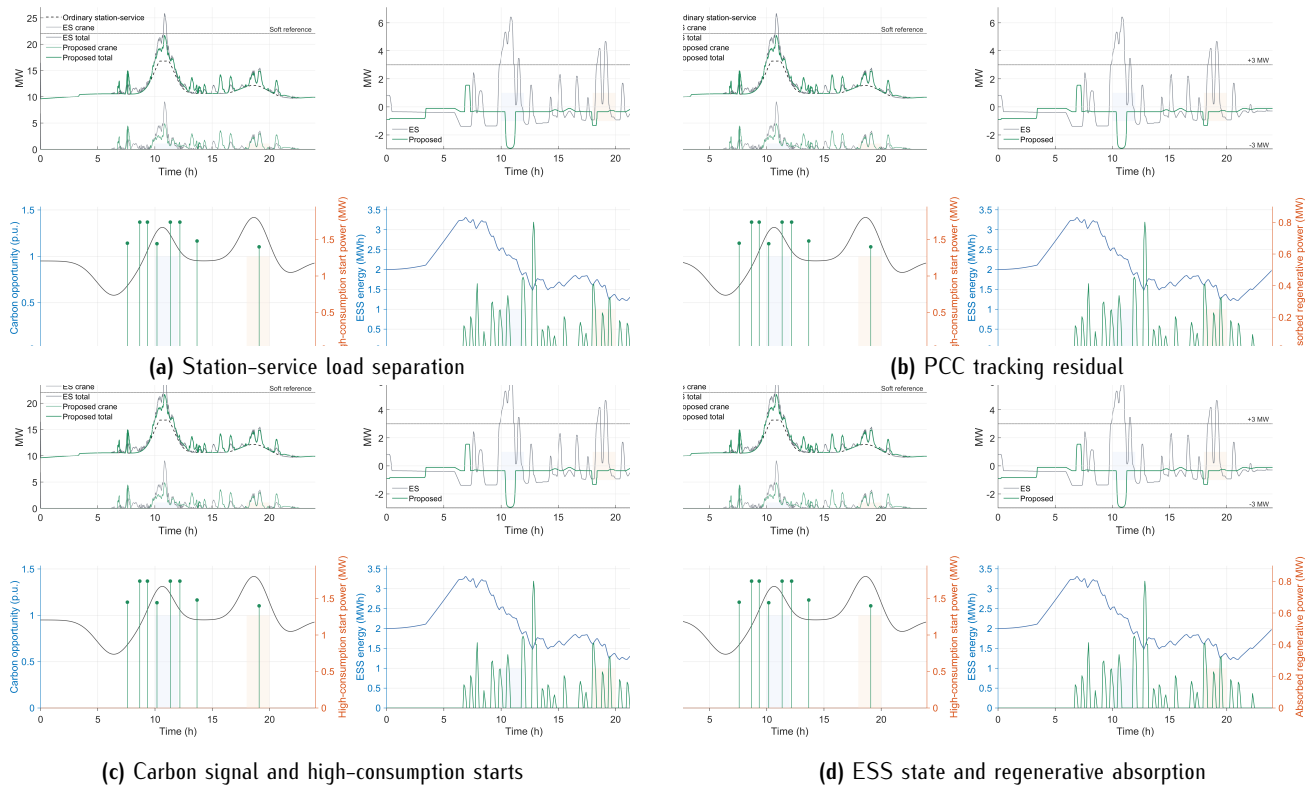


Figure 6. Representative-day station-service load and PCC residual under the compared scheduling cases

Table 5. Representative examples of task-schedule changes under Proposed

Task	Category	ES start	Proposed start	Mode change	Main reason for change	Resulting effect
Intake gate functional check	Rigid	07:30	07:30	No	Gate-safety window fixed	No flexibility used
Bridge-crane rotor inspection support	Semi-flexible	10:00	11:15	Low-speed	Avoid auxiliary peak and peak-risk interval	Peak reduced by 0.74 MW
Trash-rack lifting and lowering	Semi-flexible	10:30	13:00	No	Align lowering phase with ESS headroom	Regenerative curtailment reduced
Auxiliary material transfer	Flexible	09:45	06:45	No	Use low carbon-opportunity interval	Carbon-opportunity cost reduced
Tailwater gantry positioning	Flexible	18:15	20:30	Low-speed	Avoid AGC upward-ramp interval	PCC residual reduced
Unit-bay maintenance support	Semi-flexible	15:00	15:30	No	Avoid crane occupation conflict	Feasibility maintained

5.6. Ablation analysis

Ablation cases remove one component at a time: the CVaR peak-risk term, regenerative-energy coordination, alternative execution modes, or start-time flexibility. The remaining elements are phase-aware probabilistic forecasting, load-block placement, regenerative-energy coordination, mode selection, and low-carbon weighting.

Table 7 shows that No-CVaR increases the station-service peak from 21.3 to 22.7 MW and increases PCC RMSE from 0.69 to 0.88 MW. A small number of uncertain high-power hoisting phases account for the added residual: when the upper-tail of those tasks

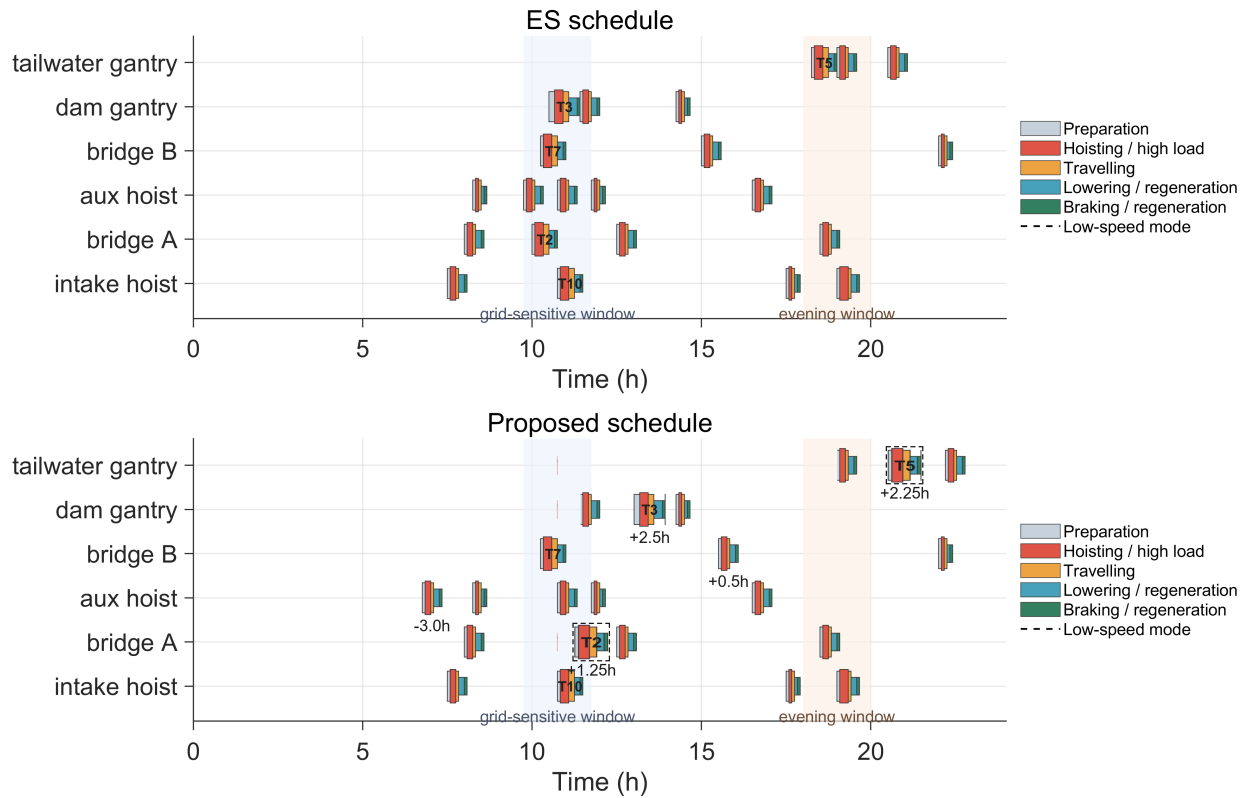


Figure 7. Gantt chart of earliest-start and proposed crane-task start times and phase-level load blocks

Table 6. Statistical comparison over 20 test days

Case	Station-service peak (MW)	PCC RMSE (MW)	95th-percentile $ \Delta P_{PCC} $ (MW)	Regenerative utilization (%)	Carbon-opportunity cost (p.u. MWh)	Average task delay (min/task)	Deadline violations
ES	25.6 ± 1.7	1.51 ± 0.28	3.94 ± 0.63	55.6 ± 8.4	56.8 ± 6.7	2.1 ± 1.5	0
ESS-MPC	23.7 ± 1.4	1.18 ± 0.22	3.18 ± 0.52	72.3 ± 7.1	54.1 ± 6.1	2.1 ± 1.5	0
PF-MILP	22.4 ± 1.1	0.91 ± 0.18	2.48 ± 0.41	79.2 ± 5.8	47.5 ± 5.2	14.8 ± 4.6	0
GF-MILP	22.0 ± 0.9	0.82 ± 0.16	2.31 ± 0.36	82.4 ± 5.4	44.9 ± 4.9	15.6 ± 4.9	0
Proposed	21.3 ± 0.8	0.69 ± 0.14	1.96 ± 0.31	86.2 ± 4.7	40.6 ± 4.4	17.2 ± 5.1	0

Table 7. Ablation results over 20 test days

Case	Station-service peak (MW)	PCC RMSE (MW)	Regenerative utilization (%)	Carbon-opportunity cost (p.u. MWh)	Average task delay (min/task)	Main interpretation
Proposed	21.3 ± 0.8	0.69 ± 0.14	86.2 ± 4.7	40.6 ± 4.4	17.2 ± 5.1	All components retained
No-CVaR	22.7 ± 1.2	0.88 ± 0.19	84.9 ± 5.0	41.3 ± 4.6	14.9 ± 4.4	Upper-tail peak risk omitted
No-Regen-Co	21.8 ± 0.9	0.76 ± 0.16	68.7 ± 6.9	42.7 ± 4.8	16.8 ± 5.0	Regenerative phases not co-scheduled
No-Mode	22.0 ± 1.0	0.81 ± 0.17	83.5 ± 5.3	42.2 ± 4.7	20.5 ± 6.3	Low-speed modes forbidden
No-Flex	24.1 ± 1.5	1.31 ± 0.25	73.1 ± 6.5	50.4 ± 5.8	3.4 ± 2.0	Non-rigid start times fixed

Table 8. Sensitivity to non-rigid task flexibility-window width

Average non-rigid flexibility window	Station-service peak (MW)	PCC RMSE (MW)	Carbon-opportunity cost (p.u. MWh)	Average task delay (min/task)	Interpretation
Fixed preferred times	24.1	1.31	50.4	3.4	Start times fixed
± 0.5 h	22.8	0.97	45.2	10.1	Window ± 0.5 h
± 1.0 h	21.8	0.78	42.0	14.5	Window ± 1.0 h
± 2.0 h	21.3	0.69	40.6	17.2	Baseline window
± 3.0 h	21.2	0.68	40.2	21.6	Window ± 3.0 h

Table 9. Sensitivity to ESS capacity

ESS rating	Station-service peak (MW)	PCC RMSE (MW)	Regenerative utilization (%)	Carbon-opportunity cost (p.u. MWh)	Interpretation
No ESS	22.6	0.84	61.5	43.8	Task placement only
1 MW/2 MWh	21.8	0.75	78.4	41.7	Smaller buffer
2 MW/4 MWh	21.3	0.69	86.2	40.6	Baseline rating
4 MW/8 MWh	21.1	0.67	89.4	40.1	Larger buffer

Table 10. Sensitivity to carbon-opportunity weight

Carbon weight multiplier	Station-service peak (MW)	PCC RMSE (MW)	Carbon-opportunity cost (p.u. MWh)	Average task delay (min/task)	Interpretation
0	21.9	0.72	45.1	13.8	Carbon term off
0.5	21.5	0.70	42.3	15.5	Multiplier 0.5
1.0	21.3	0.69	40.6	17.2	Baseline weight
2.0	21.6	0.73	39.1	20.3	Multiplier 2.0
4.0	22.0	0.80	38.5	25.7	Multiplier 4.0

Table 11. Computational performance over 20 test days

Indicator	Mean	95th percentile	Maximum
Rolling MILP solution time (s)	18.6	49.4	73.8
Number of binary variables	512	704	742
Number of continuous variables	8,420	10,940	11,506
Relative optimality gap at termination (%)	0.22	0.47	0.50
Infeasible rolling problems	0	–	–

is ignored, the median-optimal placement uses the remaining electrical margin next to those peaks.

No-Regen-Co changes peak and PCC RMSE by less than CVaR removal, but reduces regenerative utilization from 86.2% to 68.7%. If lowering and braking phases occur when the ESS is full or the ordinary station-service load is low, the recoverable

energy is curtailed. Utilization then depends on whether regenerative phases meet absorption capacity at a given ESS rating.

When alternative speed modes are removed, average delay increases from 17.2 to 20.5 minutes per task. Low-speed modes change the peak of a task that cannot be

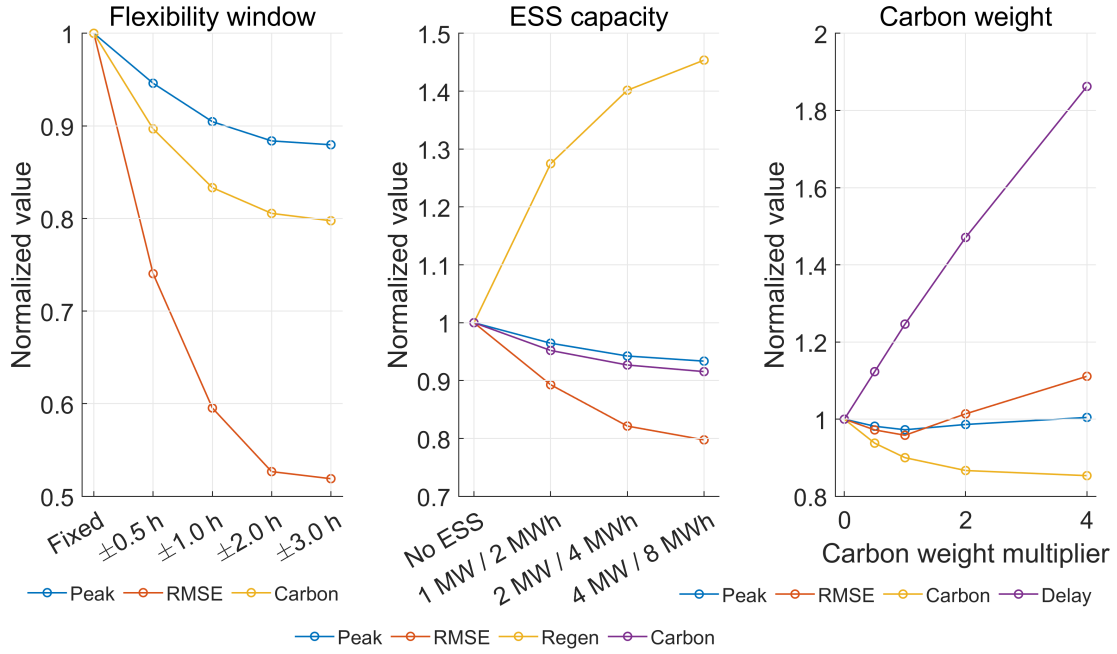


Figure 8. Sensitivity of Proposed to flexibility, ESS capacity, and carbon weight

moved far because of a narrow maintenance or gate-operation window.

No-Flex retains ESS dispatch and regenerative absorption but fixes non-rigid start times. The station-service peak rises to 24.1 ± 1.5 MW and PCC RMSE to 1.31 ± 0.25 MW. The ESS acts after task timing is fixed; start-time decisions change the timing itself.

5.7. Sensitivity analysis

Sensitivity analysis varies the average flexibility-window width of non-rigid tasks, ESS capacity, and the weight of the carbon-opportunity term. Tables 8–10 report the three sweeps, and Figure 8 summarizes the corresponding patterns.

Table 8 shows that expanding non-rigid task windows from fixed preferred times to ± 1.0 h reduces the peak from 24.1 to 21.8 MW and reduces PCC RMSE from 1.31 to 0.78 MW. Increasing flexibility from ± 2.0 h to ± 3.0 h changes the peak and PCC RMSE by 0.1 MW and 0.01 MW and increases average delay.

Table 9 shows that moving from no ESS to 1 MW/2 MWh raises regenerative utilization from 61.5% to 78.4%. Increasing the ESS from 2 MW/4 MWh to 4 MW/8 MWh changes the peak by 0.2 MW, PCC RMSE by 0.02 MW, and regenerative utilization by 3.2 percentage points. The remaining constraints at that rating are safety windows and task precedence.

Table 10 shows that a carbon-weight multiplier of 1.0 lowers carbon-opportunity cost relative to the carbon-blind case while the station-service peak and PCC

RMSE remain within 0.6 MW and 0.03 MW of that case. A multiplier of 4.0 further lowers carbon-opportunity cost to 38.5 p.u. MWh and raises the peak to 22.0 MW, the PCC RMSE to 0.80 MW, and average delay to 25.7 min/task.

The same sweep shows that the grid-facing indicators are stable under a wide change in the amplitude of γ_t . Writing Eq. (35) as $\gamma_t = 1 + A(\varphi_t - \bar{\varphi})$ with $A = (\kappa - 1)/[1 + (\kappa - 1)\bar{\varphi}]$, the carbon term separates into $\lambda_c \Delta t \sum_t P_t^{\text{ctrl}}$ and $\lambda_c A \Delta t \sum_t (\varphi_t - \bar{\varphi}) P_t^{\text{ctrl}}$. Task placement is driven by the second sum, in which the spread and the carbon weight enter only through the product $\lambda_c A$. The multipliers 0, 0.5, 1.0 and 2.0 correspond to equivalent signal ranges of 1.00, 0.79–1.21, 0.58–1.42 and 0.16–1.84 p.u. Over that span the carbon-opportunity cost falls by 13.3%, from 45.1 to 39.1 p.u. MWh, while the station-service peak moves by 0.6 MW and the PCC RMSE by 0.04 MW.

5.8. Computational performance and operational feasibility

The rolling optimization is solved at each 15-minute decision epoch with an 8-hour look-ahead horizon and 30 forecast scenarios. Table 11 reports the corresponding solution times, model sizes, terminal gaps, and infeasibility count. The number of binary variables depends on the number of pending tasks and feasible start positions; after scenario expansion, the test-set problems contain on average 512 binary variables and 8,420 continuous variables, with maxima

of 742 and 11,506 (Table 11). The model is implemented as the mixed-integer linear program stated in (33) and solved by a commercial solver with a relative optimality gap of 0.5%. Only the first scheduling interval is implemented before the forecast and operating state are updated.

The maximum solution time of 73.8 seconds is below the 15-minute decision interval. No rolling problem is infeasible on the test set: rigid tasks are fixed or protected by high-priority constraints, and non-rigid tasks carry flexibility windows and delay penalties.

The computation time is dominated by binary task-placement variables rather than by continuous ESS dispatch.

On the test days the station-service peak, the PCC residual and the carbon-opportunity cost move together when task-level forecast uncertainty, safety-feasible load-block placement and the station-level electrical terms are used jointly. Removing forecast uncertainty, start-time flexibility, regenerative coordination, or the carbon-opportunity term changes those indicators in the directions reported in Tables 7–10.

5.9. Actual-station replay test using real-time data

The previous subsections evaluate the proposed formulation on a station-oriented digital validation case. Whether the proposed method retains its performance when real-time data of the actual station are used remains to be examined. In order to verify this point, this subsection presents an actual-station replay test. Real-time data here means the native 1 s station-service, feeder, PLC and PCC recordings, together with the matching event logs. These recordings were archived and are replayed. The test is therefore an archive replay. The archive covers 15 March 2024 to 15 March 2026 (730 calendar days, 70,080 fifteen-minute intervals). Electrical curves retain phase power levels, phase durations, interval energy and threshold-crossing counts. Work orders, nameplate data, safety rules, gate events and reservoir levels are retained as recorded. The raw archive is not distributed.

The plant time reference is the GPS/BeiDou IRIG-B clock of the computer-monitoring LCUs. As shown in Table 12, each channel that enters the forecasting or scheduling model is listed with its source system, native period, clock offset and recording status. Station-service, unit-output and PCC channels are archived at 1 s. AGC set-points arrive on a native 5 s cycle. An additional 1–2 s communication delay from command to unit response is not folded into the clock offset. Feeder protection devices and drive or PLC words are also archived at 1 s. After the 2024–2025 drive upgrades, the PLC offset is within 2 s in the powerhouse and 5 s on dam-area devices. From March to July 2024 the drives used a local clock, and the offset ranged from

–58 s to +47 s. The EAM work-order system is not synchronized. The largest envelope mismatch against feeder power is 30 min, and the timestamps are left unshifted. Gate SOE events stay within 2 s. Work-permit confirmations stay within 10 min.

On the representative days used below, each day contains 518,400 one-second samples each of unit output and feeder power, 86,400 samples each of station-service load and PCC injection, 17,280 native AGC set-points, and 259,200 gate-position samples. The 24-month 15 min series has 70,080 points per channel. The series is labeled at the interval end so that it coincides with the TMR freeze. One SCADA failover from 21 September 2024 12:00 to 23 September 2024 05:00 removes about 41 h of station-service, PCC and unit-output samples. During the same upgrades, PLC records are missing for three weeks to three months per device. In those windows, phase recognition falls back to feeder power, work-order start-stop times and gate events. Feeder active power remains available on all six circuits. Range, stuck-value (> 600 s constant), energy-balance and clock-audit checks are applied. Failing samples are flagged and retained. No interpolation or time-shift is applied.

The installed fleet comprises six hoisting devices: two 1000 t powerhouse bridge cranes (4266 kW each), one dam-crest gantry (2710 kW), one intake hoist (1491 kW), one tailwater gantry (1896 kW) and one auxiliary hoist in the spillway mid-gate chamber (371 kW). The aggregate rating is 15.00 MW. The regenerative-unit rating is 9.49 MW. Nameplate ratings span a factor of 11.5. Measured 15 min consumption peaks span a factor of 10.4, and regenerative peaks span a factor of 10.8. The six devices sit at five locations: the underground powerhouse, the dam crest, the intake deck, the tailwater area and the spillway mid-gate chamber. The powerhouse is an indoor gantry hall; the other four sites are outdoor or cavern-adjacent dam-area workplaces. Station-service supply is 4×16 MVA plus 2×20 MVA dam-area transformers. The 28 MW hard limit is the long-term allowable load of two 16 MVA station-service transformers at a power factor of 0.88. The 22 MW assessment threshold is the plant rule that blocks the 1000 t and dam-crest main hoists when the 15 min station-service mean exceeds that value.

The archive contains 396 work orders on 319 days, and at most three orders appear on any day. Among them, 95 are rigid, 87 are semi-flexible and 214 are flexible, of which 26 are mandatory low-speed lifts. Seventy-five precedence relations and 95 work permits are retained. Slack is defined as deadline minus release minus duration. The mean slack is 0.50 h for rigid tasks, 2.0 h for semi-flexible tasks and 8.93 h for flexible tasks. It can be seen that 301 orders have at least 1 h of slack and 214 have at least 4 h. These windows follow the

Table 12. Real-time measurement chain of the actual-station archive
Clock offsets are stated relative to the station GPS/BeiDou IRIG-B reference

Channel	Source	Native period	Clock offset	Status
Station-service, unit output, PCC	SCADA	1 s	0 (reference)	Recorded; 41 h failover gap
AGC set-point	AGC	5 s	≤ 1 s; +1–2 s to the unit	Recorded, exogenous
Crane feeder power	Feeder protection	1 s	≤ 1 s in-house; ≤ 2 s dam area	Recorded, six circuits complete
Drive / PLC words	Crane PLC	1 s	≤ 2 –5 s after upgrade; –58 to +47 s in Mar.–Jul. 2024	Recorded; upgrade gaps of 3 weeks–3 months
Work orders (EAM)	Maintenance system	Event, 1 min	Not synchronized; up to 30 min vs. feeder envelope	Recorded, unshifted
Gate SOE / work permits	Gate and permit systems	Event	≤ 2 s / ≤ 10 min	Recorded
TMR settlement meters	Energy metering	15 min freeze	≤ 1 s	Recorded
Ordinary load excluding cranes	SIS difference	15 min	–	Derived: $P^{ss} - \sum p^m$

Table 13. Actual-station fleet and work-order archive

Item	Value	Remark
Devices / classes / locations	6 / 5 / 5	Powerhouse, dam crest, intake, tailwater, mid-gate chamber
Nameplate ratings	15.00 MW (9.49 MW regen.)	4266, 4266, 2710, 1491, 1896, 371 kW
Nameplate / measured peak / regen. span	11.5× / 10.4× / 10.8×	15 min feeder peaks
Work orders (rigid / semi-flexible / flexible)	396 (95 / 87 / 214)	26 mandatory low-speed; 75 precedences; 95 permits
Mean slack (rigid / semi-flexible / flexible)	0.50 / 2.0 / 8.93 h	301 orders ≥ 1 h; 214 ≥ 4 h
Days with work / maximum orders per day	319 / 3	Busiest archive day has three orders
Hard limit / assessment threshold	28 / 22 MW	Two 16 MVA transformers at $\cos \varphi = 0.88$; hoist-blocking rule

rigid / semi-flexible / flexible partition in Section 2. The fleet and the work-order mix are summarized in Table 13.

Table 14 summarizes the recorded 15 min station-service envelope, the 193 intervals above the 22 MW assessment threshold, and the crane attribution of those intervals. Compared with the recorded starts, the mean coincident background peak on the six-device fleet falls from 18.87 MW to 18.59 MW. The mean reduction is 0.28 MW, the median is 0.15 MW, and the maximum is 1.60 MW. The number of non-rigid orders whose execution overlaps a background load above 21.0 MW falls from 46 to 21 (–54%). The number above 21.5 MW falls from 15 to 5 (–67%). Flexible orders, with a mean slack of 8.93 h, contribute 0.36 MW of that reduction.

Semi-flexible orders, with a 2.0 h window, contribute only 0.07 MW. Regeneration over the 24 months is 1176 MWh against 6527 MWh of crane consumption (18.0%). In the upper decile of background load the incremental crane power is on average negative. Lowering and braking phases therefore already reduce the local peak.

As recorded, the measured 15 min incremental peak is $3.49/15.00 = 23\%$ of the installed rating. The busiest archive day still has only three orders, and heavy lifts remain in the low-speed mode. Task-driven crossings of 22 MW nevertheless appear. A dimensionless ratio scales the controllable crane increment to the ordinary-load margin:

$$\rho = \frac{p_{cg,ctrl}}{p_{ss,ref} - p_{0,aux}}, \quad (36)$$

Table 14. Actual-station peak envelope and crane attribution

Indicator	Value	Remark
15 min station-service mean / max	18.20 / 23.33 MW	70,080 intervals
Days with daily peak > 21.5 MW	219 / 730	Flood-season rise of the daily peak
Intervals > 22 MW	193	31 overlap a work order
Maximum after crane feeders are removed	21.979 MW	193 of 193 crossings cleared
Work-order coverage of those intervals	31 / 193	Remaining standby load 0.385 MW
Crane-group 15 min max / incremental max	3.88 / 3.49 MW	Incremental = total – 0.385 MW standby
24-month crane energy / regenerated energy	6527 / 1176 MWh	Regeneration ratio 18.0%
21 June 2024, 1 s peak with / without cranes	22.701 / 22.316 MW	Crane share of the peak 1.7%
Seconds > 22 MW with / without cranes	4,003 / 1,260	Crane share of exceedance time 69%

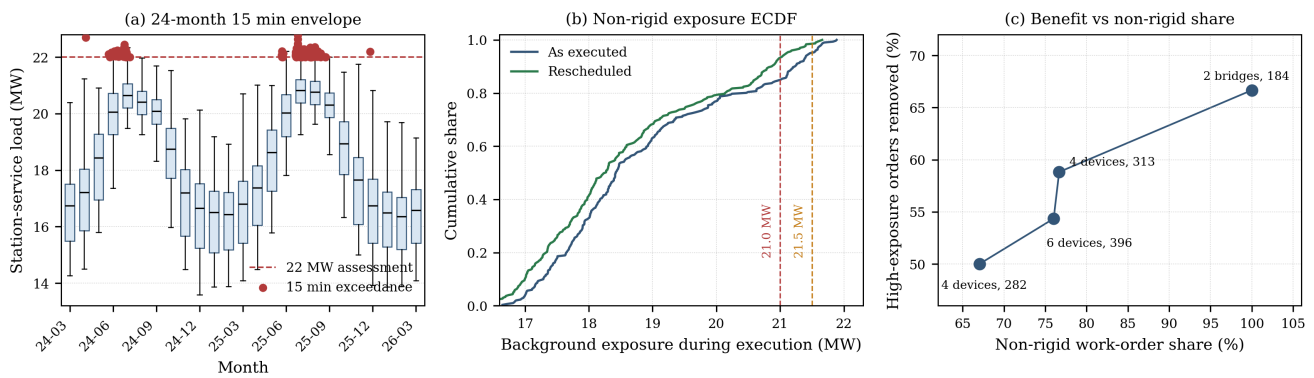


Figure 9. Actual-station archive replay

(a) Monthly 15 min station-service envelope with the 22 MW assessment line. The 193 exceedance intervals include mid-summer clusters in which only standby crane load coincides with a high ordinary-load background, and 31 exceedances that overlap a work order. (b) Cumulative distribution of the coincident background peak during the 301 non-rigid orders, as executed and after archive-constrained rescheduling. (c) Relative reduction in the number of orders coinciding with a background load above 21 MW, plotted against the non-rigid share of retained work orders on four fleet subsets.

Table 15. Archive-scale rescheduling on four fleet configurations
 ρ uses the median margin 4.16 MW to the 22 MW threshold

Fleet	Orders (non-rigid)	Rating (MW)	ρ	> 21.0 MW	> 21.5 MW
Six devices, five locations	396 (76%)	15.00	0.84	46 → 21 (-54%)	15 → 5 (-67%)
Four devices, no tailwater or auxiliary	313 (77%)	12.73	0.84	34 → 14 (-59%)	13 → 3 (-77%)
Four devices, one per class	282 (67%)	10.36	0.56	28 → 14 (-50%)	7 → 3 (-57%)
Two powerhouse bridges	184 (100%)	8.53	0.82	24 → 8 (-67%)	12 → 2 (-83%)

where $p_{cg,ctrl}$ is the controllable crane increment, $p_{ss,ref} = 22$ MW is the assessment threshold, and

the denominator is the ordinary-load margin to that threshold. On this station the median margin is

Table 16. High-duty maintenance days of the actual-station archive

Indicator	Representative day	20 high-duty days
Station-service peak, ES / Proposed (MW)	26.00 / 22.00	26.84 / 22.20
Peak reduction vs. ES (%)	15.4	17.3
Regenerative utilization, ES $\rightarrow$ Proposed (%)	63.6 $\rightarrow$ 86.7	65.6 $\rightarrow$ 90.0

4.16 MW and $\rho = 0.84$. At the first percentile of the margin the ratio is 6.62. Start-time shifting—moving a non-rigid order changes the coincident background peak and the exceedance duration—is present at both ends of that range. The five locations span an indoor powerhouse and outdoor dam-area, intake, tailwater and spillway sites. The comparison across fleet subsets covers two to six devices, one to five classes and 8.53–15.00 MW. Figure 9(c) and Table 15 order those subsets by the non-rigid share of retained work orders: a 67% non-rigid share reduces the number of orders coinciding with a background load above 21 MW by 50%, and the reduction rises to 67% when every retained order is non-rigid.

Table 16 reports the high-duty day (3 May 2025) of the actual station. On that day the station-service peak falls from 26.00 to 22.00 MW (15.4%), and regenerative utilization rises from 63.6% to 86.7%. Across the 20 high-duty maintenance days the mean peak falls by 17.3% (ES 26.84 ± 0.40 MW, Proposed 22.20 ± 0.60 MW); regenerative utilization rises from $65.6 \pm 4.9\%$ to $90.0 \pm 3.8\%$. No high-duty day violates a deadline. The replay therefore completes the recorded work on this 15.00 MW fleet while reducing the station-service peak and raising regenerative utilization.

6. Applicability

The framework rests on five structural properties rather than on a particular layout. First, crane work is issued as discrete work orders with known release times, deadlines and safety classes, so that a task can be represented as a load block with a feasible start window. Second, a non-trivial share of that work is non-rigid, so that timing is genuinely a decision variable rather than a fixed input. Section 5.9 measures that share on four fleet subsets of the actual-station archive: a 67% non-rigid share reduces the number of orders coinciding with a background load above 21 MW by 50%, and that coincidence-count reduction rises monotonically to 67% when every retained order is non-rigid. The ranking is by the non-rigid share, not by fleet size or nameplate spread. Third, task power has an internal phase sequence that recurs across instances of the same task type, so that phase-conditioned templates can be learned at all. Fourth, the station-service bus and the PCC share a measurable boundary, so that

an internal timing change has an observable grid-facing consequence. Fifth, crane feeder power and work-order events are archived on a common time base at a resolution finer than the decision grid. A station meeting these five conditions can instantiate the framework.

The same equations can be instantiated wherever the five conditions hold. The numerical changes in peak, tracking residual, and carbon-opportunity cost then depend on how much crane work coincides with the ordinary station-service peak, on the station-service limits, and on the flexibility windows allowed by maintenance rules. Table 8 reports that dependence for the flexibility-window width. The ratio ρ in (36) collects the first two of those quantities into a single scale variable. It equals 1.74 on the design case of Section 5.1 and 0.84 (median) to 6.62 (first percentile) on the actual-station archive of Section 5.9. Table 16 reports a representative-day peak reduction of 15.4% and a 20-day mean of 17.3% on that 15.00 MW fleet. Those magnitudes are not claimed for other layouts or for larger fleets. The transferable objects are the formulation, ρ , and the non-rigid-share ranking.

7. Conclusions

Hydropower-station crane groups are modeled as safety-constrained station-service flexibility resources that are forecastable and dispatchable. A PCC-coupled station-service model represents each crane operation as a phase-resolved load block. A phase-aware probabilistic forecasting layer supplies consumption and regeneration templates, together with uncertainty intervals. A rolling mixed-integer scheduler then places rigid, semi-flexible and flexible tasks and coordinates regenerative absorption and optional station-service storage. The objective reduces the station-service peak and the PCC tracking residual, and the carbon-opportunity cost, without relaxing safety, occupation or deadline constraints.

A station-oriented digital validation case reports the following indicators. Across the 20 test days, task-level rescheduling reduces the average station-service peak by 11.7% and PCC RMSE by 44.4% relative to the earliest-start baseline, without deadline violations. Adding a 2 MW/4 MWh station-service buffer raises

these figures to 16.8% and 54.3% and lifts regenerative-energy utilization from 55.6% to 86.2%. On the representative day, station-service peak demand falls from 25.84 MW to 21.67 MW and PCC RMSE from 1.58 MW to 0.71 MW. Carbon-opportunity cost falls by 22.9%–28.5%. Ablation tests attribute the changes in those indicators to the joint use of probabilistic peak-risk treatment, load-block placement, regenerative-energy scheduling, and execution-mode selection.

An archive replay then instantiates the same formulation on an actual hydropower station with a 15.00 MW installed fleet. Of the 193 assessment exceedances of 22 MW, 31 overlap a work order and the archive maximum is a working-crane interval; the remainder occur when only standby crane load coincides with a high summer background, so task placement cannot remove them all. Rescheduling the 301 non-rigid orders inside their recorded windows reduces the number of executions that overlap a background load above 21.0 MW by 54% and above 21.5 MW by 67%. The reduction is strictly monotone in the non-rigid work-order share across four fleet subsets. On a high-duty maintenance day the representative-day peak falls by 15.4% and, over 20 days, the mean peak falls by 17.3%, while regenerative utilization rises from 65.6% to 90.0%. The ratio ρ is 0.84 at the actual-station median and 1.74 on the design case.

On the test days, crane-group demand response changes regulation-margin and tracking residuals rather than bulk crane energy. Crane peaks that coincide with AGC-sensitive periods appear at the PCC as internal disturbances; moving non-rigid tasks within their flexibility windows changes those residuals. The design case and the actual-station archive together cover a 10 MW validation envelope and a 15.00 MW recorded fleet. The actual-station measurements confirm the three-class work-orders structure, the flexibility windows and the phase sequence at that fleet scale. The reported peak and regenerative-utilization changes remain those of the two cases. Subsequent work includes replication on stations with different layouts, integration with hydropower unit dispatch, and operator-in-the-loop deployment for safety-critical crane and gate operations.

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References

- [1] Vagnoni E, Gezer D, Anagnostopoulos I, Cavazzini G, Doujak E, Hočevár M, Rudolf P. The new role of sustainable hydropower in flexible energy systems

- and its technical evolution through innovation and digitalization. *Renew Energy*. 2024;230:120832.
- [2] Longhi GM, Borges CLT, Diniz AL. Demand response with load-block shifting in the day ahead scheduling of predominantly hydro systems: Impact on the large-scale Brazilian case. *Sustain Energy Grids Netw*. 2025;43:101728.
- [3] Alasali F, Haben S, Becerra V, Holderbaum W. Day-ahead industrial load forecasting for electric RTG cranes. *J Mod Power Syst Clean Energy*. 2018;6(2):223–234.
- [4] Papaioannou V, Pietrosanti S, Holderbaum W, Becerra VM, Mayer R. Analysis of energy usage for RTG cranes. *Energy*. 2017;125:337–344.
- [5] Zhao N, Schofield N, Niu W. Energy storage system for a port crane hybrid power-train. *IEEE Trans Transp Electrification*. 2016;2(4):480–492.
- [6] Kłodawski M, Jachimowski R, Chamier-Gliszczyński N. Analysis of the overhead crane energy consumption using different container loading strategies in urban logistics hubs. *Energies*. 2024;17(5):985.
- [7] Zajac P. Modelling the energy intensity of an overhead crane in a specified work cycle. *Energies*. 2025;18(24):6550.
- [8] Alasali F, Haben S, Becerra V, Holderbaum W. Optimal energy management and MPC strategies for electrified RTG cranes with energy storage systems. *Energies*. 2017;10(10):1598.
- [9] Alasali F, Haben S, Holderbaum W. Energy management systems for a network of electrified cranes with energy storage. *Int J Electr Power Energy Syst*. 2019;106:210–222.
- [10] Alasali F, Haben S, Holderbaum W. Stochastic optimal energy management system for RTG cranes network using genetic algorithm and ensemble forecasts. *J Energy Storage*. 2019;24:100759.
- [11] Kusakana K. Optimal energy management of a retrofitted rubber-tyred gantry crane with energy recovery capabilities. *J Energy Storage*. 2021;42:103050.
- [12] Kusakana K, Phiri SF, Numbi BP. Optimal energy management of a hybrid diesel generator and battery supplying a RTG crane with energy recovery capability. *Energy Rep*. 2021;7:4769–4778.
- [13] Takalani RLE, Masisi L. Development of an optimal port crane trajectory for reduced energy consumption. *Energies*. 2023;16(20):7172.
- [14] Alhazza KA. Energy efficient control of an overhead crane by optimizing a smooth waveform command shaper. *J Vib Acoust*. 2025;148(2):021002.
- [15] Fan B, Zhang Y, Sun L, Wang L, Liao Z. Passivity and underactuated modeling-based load energy coupling control for three-dimensional overhead crane systems. *Mechatronics*. 2023;96:103062.
- [16] Tan C, Yan W, Yue J. Quay crane scheduling in automated container terminal for the trade-off between operation efficiency and energy consumption. *Adv Eng Inform*. 2021;48:101285.
- [17] Li H, Li X. A branch-and-bound algorithm for the bi-objective quay crane scheduling problem based on efficiency and energy. *Mathematics*. 2022;10(24):4705.
- [18] Wen D, Li X, Ren X, Ji M, Long Q. Optimisation of berth and quay crane joint scheduling considering efficiency

- and energy consumption. *Int J Shipp Transp Logist.* 2023;17(4):487–505.
- [19] Chargui K, Zouadi T, Sreedharan VR, El Fallahi A, Reghioui M. A novel robust exact decomposition algorithm for berth and quay crane allocation and scheduling problem considering uncertainty and energy efficiency. *Omega.* 2023;118:102868.
- [20] Luo Y, Liang X, Zhang Y, Tang K, Li W. Energy-aware integrated scheduling for quay crane and IGV in automated container terminal. *J Mar Sci Eng.* 2024;12(3):376.
- [21] Hsu HP, Wang CN, Dang TT. Simulation-based optimization approaches for dealing with dual-command crane scheduling problem in unit-load double-deep AS/RS considering energy consumption. *Mathematics.* 2022;10(21):4018.
- [22] Cuong HM, Tuan LA. Robust control of rubber-tyred gantry cranes with structural elasticity. *Appl Math Model.* 2023;117:741–761.
- [23] Kou P, Gao F. A sparse heteroscedastic model for the probabilistic load forecasting in energy-intensive enterprises. *Int J Electr Power Energy Syst.* 2014;55:144–154.
- [24] Siano P. Demand response and smart grids—A survey. *Renew Sustain Energy Rev.* 2014;30:461–478.
- [25] Parvania M, Fotuhi-Firuzabad M, Shahidehpour M. ISO's optimal strategies for scheduling the hourly demand response in day-ahead markets. *IEEE Trans Power Syst.* 2014;29(6):2636–2645.
- [26] Bao Y, Xu J, Feng W, Sun Y, Liao S, Yin R, Jiang Y, Jin M, Marnay C. Provision of secondary frequency regulation by coordinated dispatch of industrial loads and thermal power plants. *Appl Energy.* 2019;241:302–312.
- [27] Fleschutz M, Bohlayer M, Braun M, Henze G, Murphy MD. The effect of price-based demand response on carbon emissions in European electricity markets: The importance of adequate carbon prices. *Appl Energy.* 2021;295:117040.
- [28] Park B, Dong J, Liu B, Kuruganti T. Decarbonizing the grid: Utilizing demand-side flexibility for carbon emission reduction through locational marginal emissions in distribution networks. *Appl Energy.* 2023;330:120303.
- [29] Sousa J, Soares I. The effect of demand response on CO₂ emissions in the Iberian electricity market: Combining economic and environmental perspectives. *Energy Clim Change.* 2023;4:100093.
- [30] Koenker R, Hallock KF. Quantile regression. *J Econ Perspect.* 2001;15(4):143–156.
- [31] Hu J, Luo Q, Tang J, Heng J, Deng Y. Conformalized temporal convolutional quantile regression networks for wind power interval forecasting. *Energy.* 2022;248:123497.
- [32] Pinson P, Nielsen HA, Møller JK, Madsen H, Kariniotakis GN. Non-parametric probabilistic forecasts of wind power: Required properties and evaluation. *Wind Energy.* 2007;10(6):497–516.