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***Abstract*—The optimal scheduling of hydropower generation holds significant importance to power system operation. The unique requirements of environmental constraints and the power system, depending on their respective objectives, demand distinct flow patterns. While power system stakeholders strive to optimize revenue in electricity markets, stakeholders from boating recreation seeks to identify flow ranges that optimize the boating experience. In pursuit of a win-win solution, this study aims to reconcile the interests of various stakeholders in hydropower scheduling. The maximum revenue from day-ahead electricity market is explored through an optimization process considering both plant operation constraints, boating flow constraints, water availability, and market prices. Results of real world case studies at a river in California show that the proposed approach can achieve dual objectives: maximizing market revenue while addressing boating recreation necessities. In addition, as the accuracy of electricity price forecasting and flow forecasting increase, the optimal revenue becomes increasingly advantageous to hydropower plant operators.**

***Index Terms*—hydropower flexibility, optimization, electricity market, electricity price forecasting, flow forecasting.**

I. Introduction

Hydropower plays an important role in power system due to its clean generation nature, flexibility, and fast ramping generation [1]. At the end of 2022, hydropower accounts for 28.7% of total U.S. renewable electricity generation and about 6.2% of total U.S. electricity generation [2]. However, many of the U.S. hydropower facilities are 30 to 70 years old [3], which have old water rights, thus facing the Federal Energy Regulatory Commission (FERC) re-licensing process [4]. One of the requirements during the FERC hydro relicensing process is to submit environmental effects of the proposed relicensing action and reasonable alternatives to it [5]. One of the critical hydropower relicense proceeding for boaters is flow optimization. Flow optimization sets the stage for future flows by identifying a specific range of flows that optimize boating recreation. Furthermore, pinpointing the range of flows between minimum acceptable and optimum flows helps maximize the potential number of boaters, thus helping to justify the case for establishing a release schedule that truly benefits the boating recreation community. Stakeholders, especially utilities and consultants, often begin negotiating during the design phase of boating flow optimization due to the impact of scheduled flows on power generation and market rates. In an effort to protect their interests in power generation, thanks to changes in water availability due to reduced snowpack, utilities and hydropower operators will try to change the flow regime, affecting the boating interest of recreation stakeholders. To this end, to get an win-win solution, the range of optimal flows should be calculated based on objective information about the reach including the following: flow of existing and historic boating use, site information/constraints, hydrologic analysis, and electricity market revenue. Extensive research exists in the literature that explores the optimization of hydropower flows to strike a balance between energy production and environmental concerns. For example, Jager *et al.* [6] explore the equilibrium between hydropower operation and freshwater ecosystems amidst climate change. The British Columbia Power and Hydro Authority [7] explores the short-term hydropower scheduling considering both electricity market dynamics and fishing constraints. In [8], Shen *et al.* discusses the impacts, challenges and suggestions of the electricity market considering hydropower flood control constraints. Roni *et al.* [9] systematically explores hydropower's flexibility evaluation through a two-step optimization process, addressing both day-ahead and real-time electricity market considerations with varying flow requirements. Pracheil *et al.* [10] provide insights into the mechanistic connections between energy and the environment in hydropower systems, which form the basis for quantitatively assessing the trade-offs between enhanced generation flexibility and its environmental consequences. Despite a plethora of literature on hydropower flexibility in light of various environmental constraints such as fishing and flood control, there is a dearth of case studies focusing on the trade-offs between recreational and environmental considerations in hydropower flexibility such as boating. In addition, most of the existing hydropower flexibility evaluation models in the literature are deterministic, which fails to adequately capture the inherent uncertainties and variability present in real-world hydropower systems and electricity market.

To address the aforementioned challenges and bridge the existing research gap, the main contributions of this paper can be summarized as:

1) explore a real-world boating flow regime as a case study to investigate the trade-offs between recreational environmental factors in hydro electricity market flexibility, particularly in the context of boating.

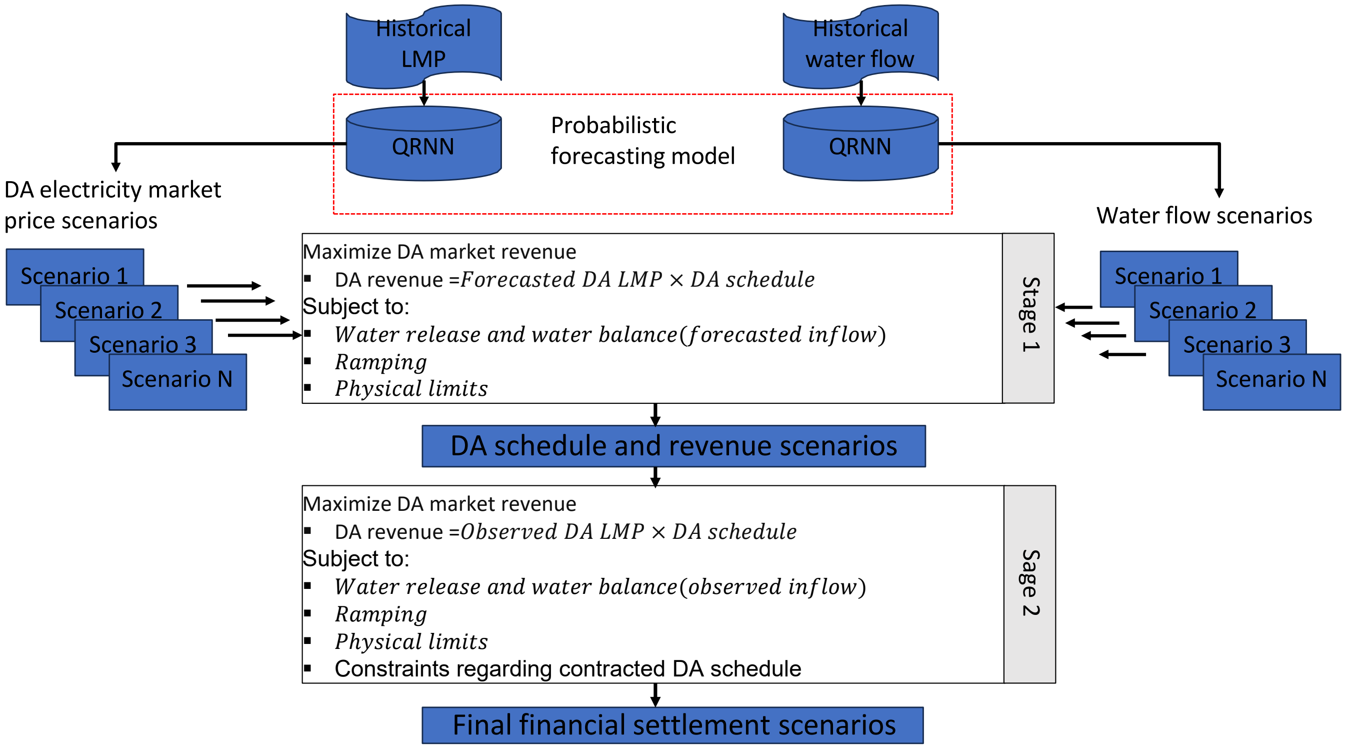

Fig. 1: Overall framework of the probabilistic hydro flexibility valuation model

2) propose a win-win solution that reconciles economic and environmental flow constraints, thereby improving environmental well-being while simultaneously optimizing revenue generation and ensuring grid requirement for clean energy at specific periods.
3) provide probabilistic insights to the timing of hydropower generation and revenue through confidence intervals. This not only aids in risk management but also contributes to informed decision-making.

The rest of the paper is organized as follows. Section II describes the proposed flow regime optimization framework, which consists of day-ahead electricity price forecasting, day-ahead outflow forecasting, and day-ahead scheduling optimization. Section III applies the developed optimal scheduling method to three scenarios at a river in California. Concluding remarks and future work are discussed in Section IV.

II. Methodology

The overall framework of the proposed probabilistic flow regime optimization methodology by considering both plant operation constraints, boating flow constraints, water availability, and market prices is illustrated in Fig. 1, which consists of three major steps: (1) day-ahead probabilistic electricity price and outflow forecasting, (2) day-ahead probabilistic scheduling optimization considering boating flow regime constraints, (3) financial settlement scenarios evaluation.

A. Day-ahead Probabilistic Flow and Electricity Price Forecasting

The Quantile regression neural network (QRNN) model has received wide attentions in recent years to explore complex nonlinear problems and provide probabilistic forecasts. There is no predictive distribution assumption for QRNN. To this end, it's a nonparametric method takes advantage of artificial neural network (ANN) and QR model. It is designed under a multilayer perceptron framework and its parameters are set by minimizing the QR error function. The architecture of QRNN model is depicted in Fig. 2,

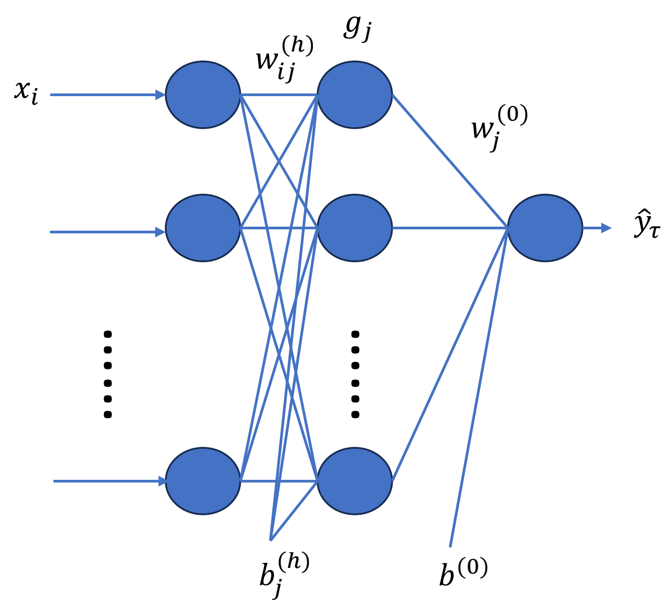

Fig. 2: Inner Structure of QRNN

where $\omega_{ij}^{(h)}$ are weights of hidden layer, $\omega_j^{(0)}$ are weights for output layer, g_j^t is the node of hidden layer, $b_j^{(h)}$ and $b^{(0)}$ are the bias for hidden and output layer, respectively. The parameters of QRNN model can be obtained by solving the following optimization problem:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \frac{1}{N} \sum_{t=1}^{N} \rho_\tau(y(t) - \hat{y}_\tau(t)) \tag{1}$$

where $\rho_\tau(\cdot)$ is the loss function expressed as:

$$\rho_\tau(\mu) = \begin{cases} (1-\tau)\mu, & \mu < 0 \\ \tau\mu, & \mu \geq 0 \end{cases} \tag{2}$$

In practice, the complexity of QRNN model is determined by the number of predictors and hidden-layer nodes, which may lead to overfitting. To avert this, the model is constrained by adding a penalty term to the approximate loss function:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \frac{1}{N} \sum_{t=1}^{N} \rho_\tau(y(t) - \hat{y}_\tau(t)) + \frac{\lambda}{IJ} \sum_{i=1}^{I} \sum_{j=1}^{J} (\omega_{ij}^{(h)})^2 \tag{3}$$

where λ is the regularization parameter, J is the number of nodes in hidden layer. In this paper, we select the energy cost, congestion cost, and their corresponding lagged variables to train the QRNN model. The outflow is calculated as the difference between downstream and upstream gage measurement.

B. Optimization Modeling

We present a two-stage framework to optimize the revenue of hydropower plants: the first stage formulates the DA schedule using forecasted inflow and LMP, while the second stage finalizes the revenue based on actual inflow and LMP.

TABLE I: Nomenclature

Sets	
T	Set of time periods for planning horizon;
$\mathcal{H}_b$	Set of time periods for boating;
Constants	
l_t^{DA}	Forecast electricity price during period t;
l_t^{R}	Observed electricity price during period t;
Q_t^{DA}	Forecast inflow at period t;
Q_t^{R}	Observed inflow at period t;
$R^{max/min}$	Maximum/minimum water release requirement;
$R^{U/D}$	Maximum ramping up/down rate at period t;
R^b	Boating release requirement;
α	Conversion efficiency;
R_t^{DA}	The contracted day-ahead schedule at period t;
Variables	
R_t	Water release at period t;
P_t	Water spillage at period t;
S_t	Reservoir storage at period t;
R_t^R	The portion of release contributes to revenue;

1) Day-Ahead (DA) Scheduling using Forecast Input: In the first stage, given forecasted inflow and LMP, we employ a linear programming optimization model to maximize revenue in the DA market over the horizon T. The model includes the following variables: hourly reservoir water release (R_t^{DA}), hourly reservoir water spillage (P_t^{DA}), and hourly water storage (S_t^{DA}). We have summarized important notations of the model in TABLE I. The objective function is expressed by:

$$\max_{R_t, P_t} \sum_{t \in T} f(R_t) l_t^{DA}, \tag{4}$$

where coefficient l_t^{DA} denotes forecasted DA LMP at hour t. The function $f(R_t)$ calculates the electricity generation derived from the release R_t using a conversion efficiency. Utilities typically determine this efficiency by comparing the water's theoretical power potential with the measured power output. In our model, $f(R_t)$ is expressed as:

$$f(R_t) = \alpha R_t \tag{5}$$

where the conversion efficiency, denoted by α, is provided by a utility. The model assumes that the hydropower plant operates under regulatory water release constraints, water balance constraints, ramping constraints, and non-negative constraints. These constraints are detailed below. **Regulatory water release constraints**: The requirements of reservoir operating ranges and boating regime are the primary regulatory constraints. Constraint (6) outlines the release capabilities. Constraint (7) specifies boating release for April, May, and Labor Day:

$$R^{min} \leq R_t \leq R^{max}, \tag{6}$$

$$R_t = R^b, t \in \mathcal{H}_b, \tag{7}$$

Water balance constraint: The reservoir's water balance during period t is given by constraint (8):

$$S_t - S_{t-1} = Q_t - R_t - P_t \tag{8}$$

where parameter Q_t is the forecast inflow during period t.

Ramping constraints: Constraint (9) and (10) are the upper bounds for hourly up-ramping and down-ramping rates, respectively:

$$R_t - R_{t-1} \leq R^U, \tag{9}$$

$$R_{t-1} - R_t \leq R^D, \tag{10}$$

where parameter R^U and R^D denote ramp-up and ramp-down limit.

Non-negativity constraints: constraint (11) ensures all variables are non-negative:

$$R_t, S_t, P_t \geq 0. \tag{11}$$

2) Final Revenue Calculation: In the second stage, schedules are tuned based on observed water flow, building upon the day-ahead schedules. It's important to note that the power eligible for revenue cannot be larger than the contracted day-ahead schedule. To enforce this, the stage-2 model introduces the following release constraints:

$$R_t^R \leq R_t, \tag{12}$$

$$R_t^R \leq R_t^{DA}, \tag{13}$$

where the variable R_t^R represents the portion of the actual release, denotd by R_t, contributing to the revenue. The parameter R_t^{DA} denotes the contracted day-ahead schedules which are the optimal release of the stage-1 model.

Furthermore, the stage-2 model accounts for all the operational constraints in the first stage. A notable modification in the stage-2 model is the substitution of forecasted inflow with the observed inflow in the water balance constraint. The problem formulation for this stage is defined as:

$$\max_{R_t^R, R_t, P_t} \sum_{t \in T} f(R_t^R) l_t^{DA}, \tag{14}$$
$$\text{s.t. } (6), (7), (8), (9), (10), (11), (12), (13).$$

III. Case Study and Results

The effectiveness of the probabilistic optimal scheduling method is evaluated through case studies at a site in California. In this work we adopt the DA and RT electricity price collected from California Independent System Operator (CAISO) for the year 2020-2022 [11]. These DA and RT electricity prices represent wholesale prices. The outflow through the powerhouse is calculated using gage data from USGS dashboard.

A. Benchmarks and comparison settings

In the paper, four different probabilistic forecasting models are compared in the case studies. The three benchmark probabilistic forecasting methods are quantile regression (QR), quantile regression forests (QRF), and persistence method (PS). The persistence probabilistic forecasting method takes the recent observations to estimate the mean and variance and generate Gaussian distribution for the future predictions. The reasons for choosing these three baseline models are: (i) QR, QRF, and PS are widely used models in probabilistic forecasting, which allows us to explore different models; (ii) since a hybrid QR-based model is adopted, it is important to compare its accuracy with single QR method and other hybrid QR-based models such as QRF.

Three case study scenarios are compared in this paper (i) The first scenario involves the consideration of boating flow regime constraints alongside other regulatory flow requirement constraints. (ii) The second scenario focuses exclusively on regulatory flow requirement constraints. (iii) The third scenario involves no optimization, with hydropower revenue calculated by the summation of hourly generation multiplied by the corresponding hourly LMP.

B. Probabilistic Forecasting Results

Based on different needs, probabilistic forecasts may be required in discrete forms (e.g., quantiles) or continuous forms (e.g., probability distribution). For the measurement of continuous variables, the continuous ranked probability score (CRPS) is one of the most popularly used comprehensive evaluation scores, which evaluates the quality of predictive CDF and is expressed as:

$$CRPS = \frac{1}{N} \sum_{t=1}^{T} \int_{-\infty}^{+\infty} (F_t(x) - H(y_t \le x)^2 dx \tag{15}$$

where F_t is the CDF of the predictive distribution at t, y_t denotes the observation, $H(\cdot)$ is a Heaviside function, and T is the sample size. CRPS is a generalized case of mean absolute error in the probabilistic fashion. Therefore, a lower CRPS indicates a better probabilistic forecast.

To evaluate the probabilistic forecasting models in this work, the CRPS values of different models are compared in Table II. Results show that the proposed QRNN model has the smallest CRPS values compared to other benchmark models.

TABLE II: CRPS of different models

Model	CRPS	I_{CRPS} [%]
QRNN	**3.60**	N/A
QRF	3.99	10.80
QR	5.33	48.05
PS	5.72	58.88

Note: The smallest CRPS values are in boldface.

C. Optimization Results

We summarize the stage-1 and stage-2 revenues of the 3 cases for the year 2021 in Table III. Case 1, influenced by the boating constraint, has lower stage-1 and stage-2 revenues across all percentiles than Case 2. This constraint also results in a narrower distribution of revenues across the two stages in Case 1. We next analyze the optimal solutions for the two stages in Case 1 in detail.

1) Analysis of stage-1 results: Fig. 3 displays a dual-axis box plot, illustrating the monthly distribution of the stage-1 optimal release (blue boxes) and revenue (green boxes) across 99 scenarios. The monthly release fluctuates between 7400 and $400,000$ cfs, while the monthly revenue ranges from 0.02 to 1 million. A seasonal trend is observed in both release and revenue, peaking from June to August. The hydropower facility examined in the numerical study has a modest reservoir, capable of storing water equivalent to one month's supply during wet seasons. The release demonstrates relatively consistent variability throughout the year, whereas revenue exhibits greater variability, particularly from June to August. The presented distributions of release and revenue offer the overview of potential outcomes and their respective probabilities, providing operators with richer insights for decision-making.

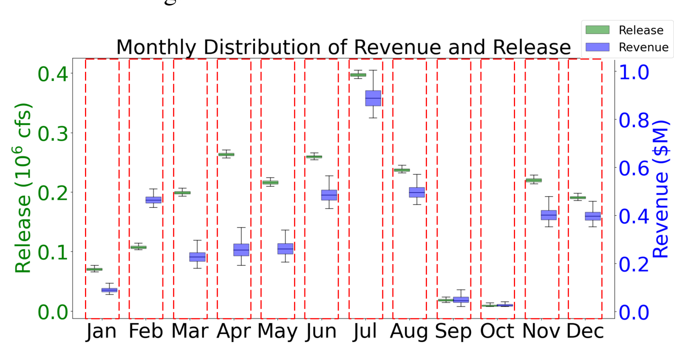

Fig. 3: Monthly distribution of stage-1 optimal release and revenues.

TABLE III: Distribution of the yearly revenue under 3 cases. S1 and S2 denotes the revenues of stage 1 and stage 2, respectively. Units of the revenues are in $\$10^6$.

Revenue	Case 1		Case 2		Case 3	
	S1	**S2**	**S1**	**S2**	**S1**	**S2**
Minimum	3.513	2.830	3.444	2.871	2.152	2.877
25th percentile	3.834	2.877	3.945	2.952	2.680	2.940
Median	4.033	2.906	4.150	2.983	2.896	2.961
75th percentile	4.253	2.927	4.371	3.008	3.122	2.972
Maximum	4.828	2.968	4.947	3.056	3.716	2.987

2) Analysis of stage-2 results: Fig. 4 displays the monthly distribution of stage-2 optimal results for boating flow regime constraints alongside other regulatory flow requirement: release (blue boxes) and revenue (green boxes) spanning the 99 scenarios. Similar to the stage-1 findings, a seasonal trend is recognized in both release and revenue, which peak during the months of June to August. In contrast to the stage-1 results, the stage-2 optimal release and revenue demonstrate minimal and consistent variability throughout the entire year.

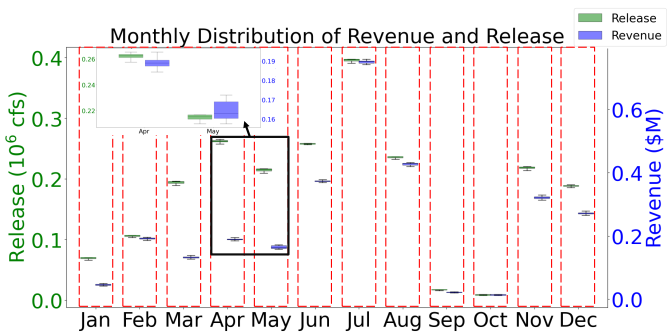

Fig. 4: The monthly distributions of stage-2 optimal release and revenues across the entire year show very low variability. We zoom into April and May (boating season) to show detailed result.

IV. Conclusion

This paper developed a probabilistic hydropower flexibility valuation model to provide a mutually beneficial solution that effectively balances economic considerations with environmental constraints related to boating flow regime at a river in California. Results of the case study under different constraints and probabilistic forecasting models showed that: (i) A substantial disparity in revenue emerges when the genuine value of the hydropower plant is evaluated, taking into account the intricate trade-offs between meeting environmental boating flow requirements and harnessing the full potential of the power system; (ii) there exists an optimal flow regime threshold for boating, particularly for dyy months; (iii) the comparison between different probabilistic forecasting models has shown improved probabilistic forecasting accuracy likely to provide higher revenue difference after optimization. Future work will explore: (i) the market value of hydropower flexibility, with a focus on integration with battery technology, (ii) the possibilities of complementing hydropower with floating wind and floating solar farms, and (iii) scenarios encompassing different electricity market contract types and diverse environmental requirements, including flood control, the well-being of aquatic species, and irrigation needs. This multifaceted exploration will provide valuable insights into optimizing hydropower operations while safeguarding the environment.

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