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***Abstract*—Harnessing renewable energy from diverse sources is paramount for sustainable power systems. Recently, co-located floating PV (FPV) systems present an intriguing prospect in this context. These hybrid systems, blending hydro and solar power, may offer a more consistent electricity output and potential economic advantages. Yet, assessing their actual potential requires a comprehensive techno-economic assessment. In addition, probabilistic price forecasting has recently gained attention in electricity market because decisions based on such predictions can yield significantly higher profits than those made with point forecasts alone. To this end, this paper embarks on a journey to elucidate the electricity market potential of co-located hydro-FPV systems in a probabilistic fashion to investigate the technological merits and economic viability of co-located hydro-FPV under different market structures. Our preliminary findings suggest that LCOE and payback metrics are sensitive not only to different markets but also to different solar incentives. Concurrently, we also observe that the payback period is generally faster with a production tax credit (PTC) than an investment tax credit (ITC). This assessment serves as a cornerstone for understanding the future prospects of co-located hydro-FPV systems in modern electricity markets.**

***Index Terms*—floating photovoltaic, hydropower, electricity price forecasting, techno-economic analysis, sustainability.**

I. Introduction

Floating photovoltaic (FPV) systems, also known as floating solar or floating solar panels, involve installing solar panels on bodies of water such as lakes, reservoirs, ponds, and even the sea. FPVs have seen a significant increase in installation capacity, soaring from 132 MW in 2016 to 1.1 GW in 2018, with projections estimating a rise to approximately 13 GW by 2022 [1]. This growth indicates a rising global interest, with Asia leading the FPV deployment, closely followed by Europe and the US.

From the standpoint of energy generation technologies, FPV can be categorized into stand-alone FPV system and hybrid FPV system [2]. Stand-alone FPV systems are those that are operated independently and not connected or operated in hybridization with other energy generation source. Conversely, hybrid FPV systems have same FPV configuration but are coupled with other energy generation technologies. The interest in the benefits of hybrid systems, including the hybridization of FPV and hydro power has surged in recent years. Farfan *et al.* [3] estimated the global potential for FPV systems paired with hydropower installations to be between 4,400 and 5,700 GW, which corresponds to an annual generation capacity of 6,270 to 8,039 TWh for installations on reservoirs dedicated to hydropower and multipurpose reservoirs, respectively. The U.S. is actively exploring such FPV-hydropower projects, recognizing their potential for enhanced energy generation. The hybridization of FPV and hydropower helps to offset the intermittent nature of FPV power generation [4], offers additional energy storage opportunities [5], and enhances the utilization of transmission networks [6]. Furthermore, it can reduce PV curtailment [7] and reduce the costs associated with transmission system interconnections [8]. Beyond benefits for enhanced power generation, FPV-hydropower systems can also help with water management by reducing evaporation and improving water quality [9].

Beyond the potential benefits brought from FPV-hydropower system, questions remain about the actual potential for FPV-hydro systems. This includes technical potential for FPV-hydropower system deployment at different scales, and economic potential at different locations. Researchers have conducted various studies on the techno-economic assessment of standalone FPV systems as seen in the works of [10], [11]. Some researchers have broadened their scope to hybrid FPV systems with other energy sources, such as wind in [12] and hydro in [1]. Yet, there's still a notable gap in the literature regarding techno-economic assessment of hybrid FPV-hydropower system, particularly their economic performance across various location and electricity market structures in the U.S. Furthermore, the majority of current techno-economic models are deterministic, falling short in accurately representing the inherent uncertainties in electricity market behavior, particularly over the expected life of the system (20-30 years). Probabilistic forecasting has recently gained more attention in strategic planning for power systems due to its ability to quantify uncertainty [13]. Probabilistic forecasts usually take the form of prediction intervals, quantiles, or scenarios. Generally, probabilistic forecasting methods can be classified into parametric and non-parametric approaches [14], [15]. Parametric approaches require low computational cost since a prior assumption of the predictive distribution shape is made before the parameter estimation. Non-parametric approaches are distribution free, and their predictive distributions are inferred through observations or scenarios [16]. In this paper, we aim to bridge these gaps by performing techno-economic assessment of co-located hydro-FPV systems based on different electricity markets. By leveraging probabilistic electricity price forecasting, the techno-economic model can provide refined perspective, with uncertainty bounds, on the viability of FPV-hydropower system under varying market conditions. The main contributions of this paper are twofold:

1) explore the techno-economic potential of hybrid FPV-hydropower systems in U.S. reservoirs, and
2) quantify long-term market uncertainty through probabilistic electricity price forecasting

The rest of the paper is organized as follows. Section II describes the proposed techno-economic assessment framework, which consists of hydro power generation modeling, FPV generation modeling, long-term probabilistic electricity price forecasting, and techno-economic assessment. Section III applies the developed framework to four different electricity markets. Concluding remarks and future work are discussed in Section IV.

II. Methodology

There are three types of hybrid FPV-hydropower systems in the existing literature: i) Co-located hybrid systems, ii) Virtual hybrid systems, and iii) Full hybrid systems [17]. It should be noted that this work focuses on the co-located hybrid FPV-hydropower system, where FPV and hydropower are sited together to achieve cost savings, but operations are separately optimized, as showed in Fig. 1. The overall

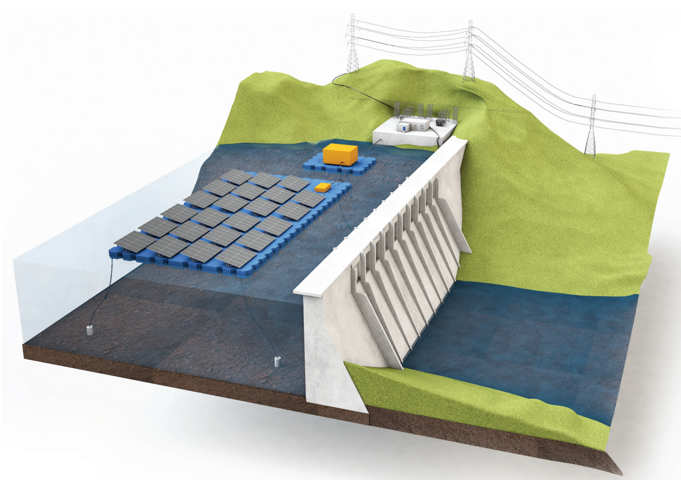

Fig. 1: Schematic plot of the co-located FPV-hydropower system

framework of the proposed FPV-hydropower techno-economic assessment tool is illustrated in Fig. 2. It consists of three major steps: (1) Co-located hydro-FPV generation modeling, (2) long-term probabilistic electricity price forecasting, and (3) techno-economic assessment and sensitivity analysis.

A. Hydropower generation modeling

To determine the hydropower generation time-series, we use the open-source Python tool code HydroGenerate V2.0 [18]. In general, the hydropower potential can be calculated based on flow and hydraulic head data, which can be expressed as:

$$P = \eta \times \rho \times Q \times H \tag{1}$$

where P denotes the hydropower potential, η denotes overall system efficiency, ρ denotes the water density, Q denotes flow, and H denotes net hydraulic head, respectively.

B. Floating PV power generation modeling

To model the FPV power generation, pvlib-python [19], an open-source python-based tool for modeling solar energy systems, is adopted. One of the major advantages of FPV is the increased efficiency due to improved thermal performance of the modules because of the indirect effect of presence of water bodies on the local ambient temperature or wind conditions [20]. The water temperature can be downloaded from the USGS databases. The cell temperature T_{cell} of the PV module is estimated using the Faiman equation [20].

$$T_{cell} = T_{water} + \frac{POA * \varrho * (1 - \zeta)}{U} \tag{2}$$

where, T_{water} is the ambient temperature of the water, POA is the plane of array, ζ is the module efficiency (set to 0.214), ϱ denotes the absorption coefficient of solar irradiation (set to 0.9), and U is the constant heat loss coefficient (set to 36). The DC power output of the PV system is obtained using pvlib-python's inbuilt single-diode model. Finally, AC power output is obtained using the DC to AC ratio of the inverters.

C. Long-term probabilistic electricity price forecasting

To approximate future electricity market information in the next 20-30 years, we adopt probabilistic electricity price forecasting, which measures the market uncertainty and therefore directly impact the techno-economic assessment. A two-step probabilistic method is adopted in this paper [14]. In the first step, the deterministic electricity price forecasts are produced by a machine learning method (i.e., support vector regression (SVR)) [14]. Specifically, a SVR model with linear kernel is adopted and the parameters of SVR are set to be δ = 0.001, ϵ = 0.001 and C = 1, where δ, ϵ, and C are free parameter, insensitive parameter, and penalty weight, respectively. Then, the uncertainty is added to the deterministic forecasts by an optimal uncertainty indicator in the second step. The procedure of probabilistic electricity price forecasting is described as follows:

1) Obtaining long-term electricity price drivers such as temperature, electricity demand, and electricity generation. In this paper, only long-term temperature forecasts data from [21] is used since temperature is by nature the driver of electricity demand and price [22]. Details about temperature data and demand data are described in III-A. Once the electricity price drivers are determined, the long-term electricity price forecasts can be generated by the trained SVR model.
2) Parameterizing the uncertainty of the electricity price in terms of μ and σ, where μ is assumed to be the

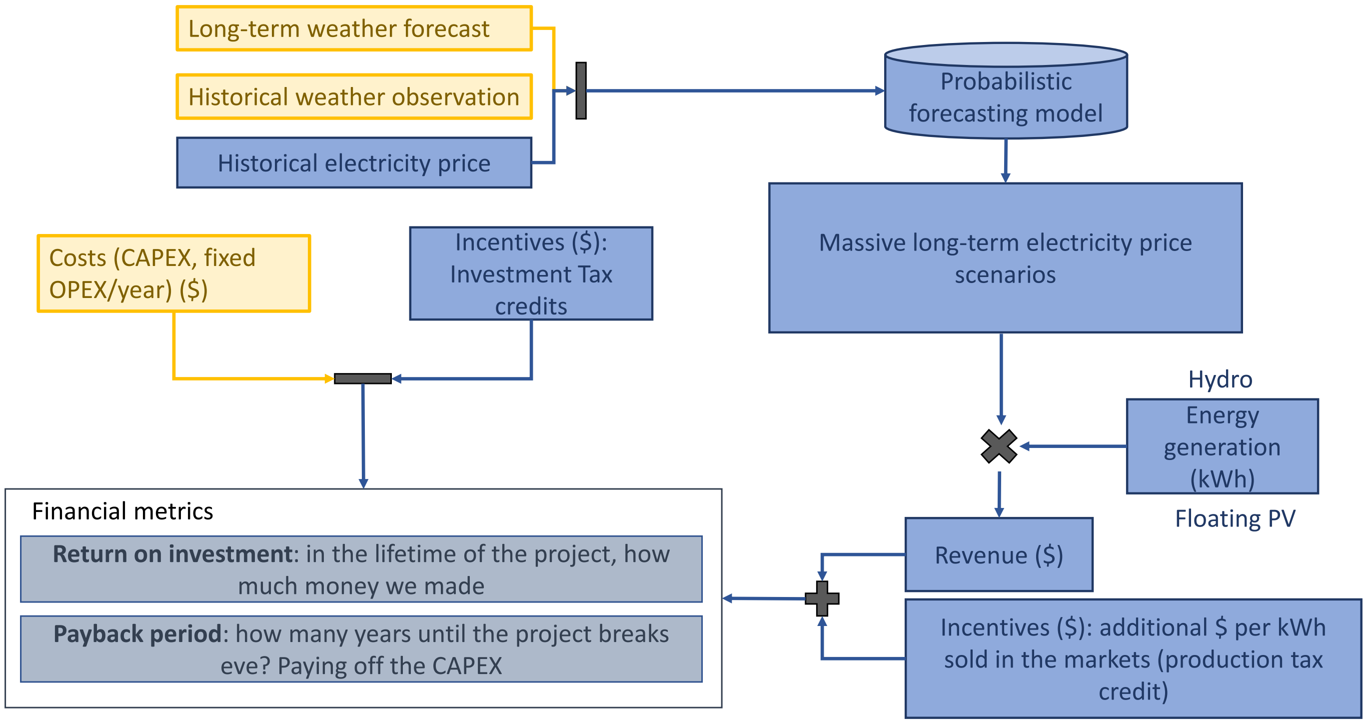

Fig. 2: Overall flowchart of the proposed method

electricity price forecast itself. Then, the quantile, q, and its corresponding pinball loss L_q , are derived and expressed by q and σ:

$$F_t(y_{p,t}|\mu_t,\sigma_t) = F_t(\sigma_t) \tag{3}$$

$$Q_t(p) = F_t^{-1}(p) = F_t^{-1}(p,\sigma_t) \tag{4}$$

$$L_{q,t}(q,\sigma_t) = q - H(y_t - Q_t(q))y_t - Q_t(q) \tag{5}$$

where t is a time index, which means the predictive distribution differs at different forecasting step; $F(\cdot)$ and $F^{-1}(\cdot)$ are a cumulative distribution function (CDF) and its corresponding inverse function, respectively; $Q(\cdot)$ is the quantile function; p and q are probability and a quantile, respectivlery; $H(\cdot)$ is the Heaviside step function. Next, the electricity price uncertainty indicator, σ (the only unknown parameter), at each forecasting time step is optimized by minimizing the averaged pinball loss of all quantiles with a genetic algorithm (GA):

3) A SVR surrogate model, Φ, is constructed to fit the actual electricity price and σ^* set y_p, σ^* in the training stage, which is used to generate unknown pseudo standard deviations, $\hat{sigma}^*$, in the forecasting stage.

The SVR model is empirically selected based on experience in [14]. Note the focus of this paper is to perform techno-economic assessment rather than building the most accurate probabilistic forecasting model.

D. Techno-economic Assessment

Once the probabilistic electricity price forecasts are generated, a large number of electricity price scenarios can be obtained through inverse sampling from the CDF of predictive distribution, which are used for the uncertainty quantification of the techno-economic assessment. The techno-economic framework is built to assess the financial performance of FPV-hydropower systems using a suite of metrics that matter to industry (e.g., levelized cost of energy (LCOE), payback period, etc).

LCOE is a metric used to calculate the average total cost to build and operate a power generation system per unit of total electricity generated over its assumed lifetime. LCOE is defined as the ratio between the total costs of a project over its lifetime, including capital expenditures (CAPEX), operational and maintenance expenditures (OPEX), and the incentives (I), to the expected energy production of the system during its operational life. The formula to calculate LCOE is given as follows:

$$LCOE = \frac{\sum_{n=0}^{N} \frac{OPEX(n) + CAPEX(n) - I(n)}{(1+r)^n}}{\sum_{n=0}^{N} \frac{P(n)}{(1+r)^n}} \tag{6}$$

where r is the discount rate, n is the year, ranging from 0 to N, N represents the project's lifetime, $P(n)$ is the electricity production in year n.

The payback period, denoted as P_γ, is a financial metric calculated as the ratio of the total installation and operational costs of a FPV-hydropower system to the revenue it generates over time.

III. Case Study and Results

We investigate how different locational marginal pricing (LMP) profiles from across the U.S. impact the techno-economic metrics of the co-located hydro-FPV system. To capture regional electricity market trends, we consider four regions: the Electric Reliability Council of Texas (ERCOT), the California Independent System Operator (CAISO), the DUKE Energy Transmission (DUKE), and the Pennsylvania-New Jersey-Maryland Interconnection (PJM). These locations were chosen to represent diverse market with unique potential of co-located hydro-FPV resource.

A. Data summary

We adopt the day-ahead (DA) electricity price collected from aforementioned locations for the year 2021. These DA electricity prices represent wholesale prices. The flow data are processed as discharge data obtained from the United States Geological Survey (USGS) National Water Database [23]. The forecasted temperature data are collected from PNNL's climate research portal [21].

Meteorological solar irradiance data for FPV power simulation is collected from the National Solar Radiation Database (NSRDB). The solar location selected for each region are Sana Rosa, CA (CAISO), Austin, TX (ERCOT), Charlotte, NC (DUKE), and New York, NY (PJM). Each location is assumed to have a 1 MW solar installation, have an inverter efficiency of 90%, an annual discount rate of 5%, and a life expectancy of 30 years.

The incentives considered are the investment tax credit (ITC) and production tax credit (PTC) listed by the department of energy[1]. We assume a ITC of 30% and a PTC of 2.75 cents per kWh for a period of 10 years.

The baseline cost associated with construction and operation of the FPV is considered to be a CAPEX of \$1.18 million per MW and a yearly OPEX of \$7,900 per MW. These prices are assumed to be the same in each market.

B. Result and discussion

By thoroughly examining key performance metrics, such as LCOE and payback period under various electricity price scenarios, this study reveals crucial insights into the system's overall performance, economic viability, and the impact of including the ITC and PTC incentives.

The LCOE results for a discount rate of 5% are depicted in Fig. 4. Here it can be seen that the LCOE, which has the same CAPEX/OPEX cost across the markets, and doesn't depend on electricity pricing, is still different in each market. This is due to the amount of solar generation at each location, i.e. there is more solar production in CAISO than the other markets. These results show an increment of approximately 16% in LCOE when compared to a land-based solar system of the same size. This difference is increased by considering

[1]https://www.energy.gov/eere/solar/federal-solar-tax-credits-businesses

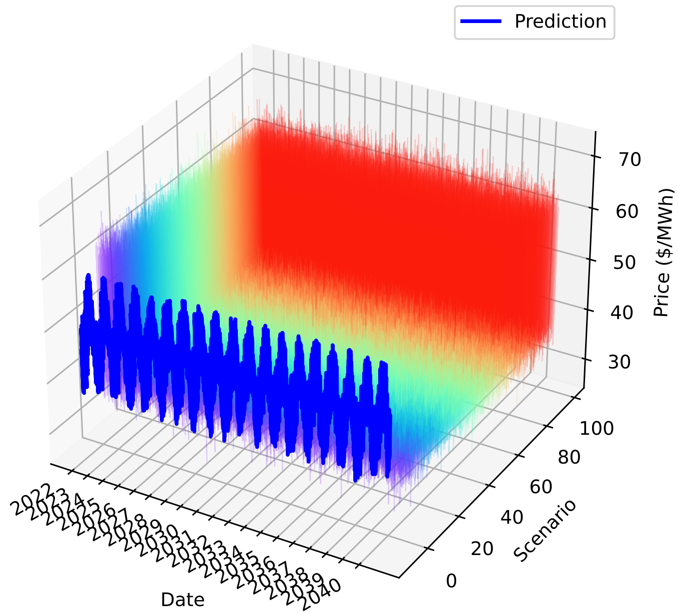

Fig. 3: Long-term electricity price scenarios at CAISO. Figure is Representative all all markets.

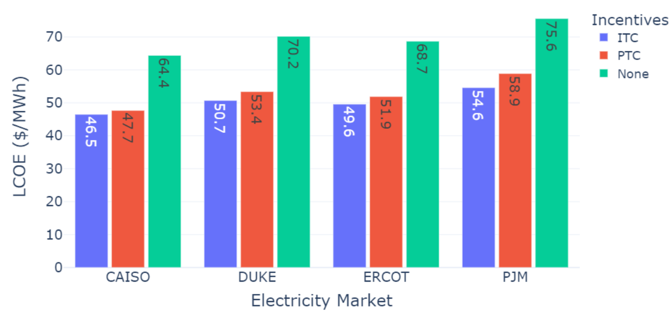

Fig. 4: The LCOE sensitivity for different markets and when consideging the ITC, PTC, and no incentives. A discount rate of 5% was considered with a life expectancy of 30 years.

higher discount rates (which could happen if kept in pace of the nation's interest rates) of up to 8.5%. If this is the case, the LCOE across every market will increase approximately 25%.

The payback period in years for each market with ITC, PTC, and no incentives is shown in Fig. 5. Here, we use 100 different pricing scenarios as illustrated in Fig. 3 for each market and therefore have a range of potential payback periods, which depends mainly in the uncertainty in the electricity price forecast. It can be seen that CAISO has the shortest payback period due to it's larger solar generation, and the higher cost of electricity in this market. Furthermore, it can be seen that the ITC and PTC have overlap in the payback period, however, the PTC tends to have a shorter payback period and therefore would be considered financially more attractive.

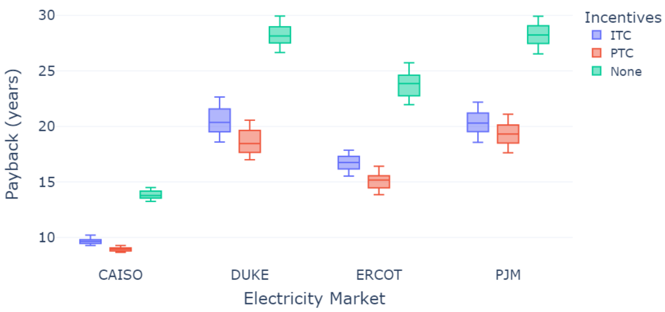

Fig. 5: The payback period sensitivity using 100 pricing scenarios for each market and ITC, PTC, and no incentives.

IV. Conclusion

In this research, we conducted a comprehensive techno-economic assessment of electricity market potential for co-located hydro-FPV systems with different incentive considerations. It was demonstrated that LCOE and payback metrics are sensitive not only to different markets but also to the selection of solar incentives. A key takeaway is that the payback period is generally faster with a PTC over an ITC incentive.

Potential future work will include techno-economic assessment for full hybrid FPV systems with wind, hydro, and battery. Also, both cost and power generation improvements will be explored through co-optimized planning and operation.

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