

Optimal Complementarity Analysis of Potential Floating Solar Co-Located With Existing Hydropower Assets Across the Contiguous United States

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This work was supported in part by Battelle Energy Alliance, Limited Liability Company (LLC), under Contract DE-AC07-05ID14517; in part by the University of Tennessee (UT) UT-Battelle, LLC, through the U.S. Department of Energy (DOE), under Contract DE-AC05-00OR22725; and in part by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy through the Solar Energy Technologies Office under Award 39263.

ABSTRACT The U.S. is expected to double its rate of renewable capacity from 2024 to 2030. However, the stochastic nature of renewable energy poses challenges to the operation and reliability of our power grid. The combined generation from renewable energy sources, with dispatchable sources (such as hydropower) operating as a hybrid energy plant, could mitigate this variability. In this paper, the complementarity analysis of selected U.S. reservoirs with existing hydropower assets (EHAs) and potential floating photovoltaics (FPVs) is conducted for the continuous U.S. (CONUS). The optimal FPV capacity for each site is determined by minimizing the variability of the combined output, while adhering to the FPV potential. Our results indicate that over 50% of the analyzed reservoirs achieve a stability coefficient exceeding 0.5, leading to a less-variable output after optimization. Finally, we analyze the complementary hydro-FPV hybrid reservoirs by considering both the Pearson correlation coefficient and the stability coefficient on daily, monthly, and yearly scales. Summaries are included of locations of theoretical FPVs co-located with hydropower plants that exhibit high complementarity based on the selected metrics.

INDEX TERMS Complementarity analysis, hybrid system, hydropower, floating PV.

I. INTRODUCTION

ACCORDING to the International Energy Agency's (IEA) 2024 renewables market report [1], global renewable energy capacity is projected to increase by 270% by 2030, with nearly 940 GW of new renewable capacity coming online each year.

While the stochastic characteristic of variable renewable energy (VRE) challenges the reliability of electricity system operation with uncertainties, the combined output from a hybrid energy plant can be less variable [2], [3]. Beyond smoothing out output uncertainty, the benefits of hybridizing energy systems include reducing the need for new transmission lines and infrastructure, improving energy efficiency, and lowering shared operation and maintenance costs [4].

The term complementarity can be defined as the temporal anti-correlation of co-located energy sources [4], [5]. In other words, the combined output of co-located complementary resources will be less variable within the observed period [6]. To quantify complementarity between two sources of renewable energy, statistical correlation metrics are widely used, such as Pearson correlation coefficient [5], [7], Spearman's rank correlation [8], [9], and Kendall's Tau correlation [10], [11]. More metrics were proposed, particularly for evaluating energetic complementarity. For example, Sterl et al. [12] proposed the stability coefficient that quantifies the added value of the hybridized power to the based power in terms of balanced daily output. Murphy et al. [4] evaluated the daily complementarity among solar, wind, and hydropower across the contiguous U.S. (CONUS) based on such statistical

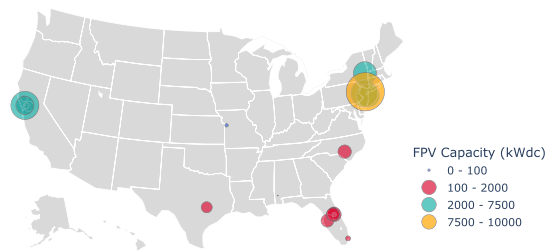


FIGURE 1. FPVs deployed in the U.S. as of 2024.



FIGURE 2. The largest FPV project in North America, in Canoe Brook Reservoir, with a total of 8.9 MW. Image credit: NJR Clean Energy Ventures.

correlation metrics as the Pearson correlation coefficient and the stability coefficient. Among the combinations of these three sources, it was observed that hydro-solar had the highest complementarity, especially in the Northeast, for both existing hydropower assets (EHAs) and non-powered dams. For solar and existing hydropower complementarity, the roadmap illustrations of both metric values are provided in [4] under the assumption of 1:1 ratio of nameplate capacity.

Compared to conventional ground-mounted photovoltaic, technoeconomic analysis prizes floating photovoltaics (FPVs) primarily for their reduced land requirements, enhanced energy production, and added water-conservation benefits [6]. The current landscape of FPV in the US is limited to private, state, and municipal water bodies, with a total of 26 projects at the time of this writing. As illustrated in Fig. 1, the average capacity across the projects is approximately 1.4 MW, with most of the projects centered in California, Florida, and New Jersey. The largest FPV deployment is located in New Jersey's Canoe Brook Reservoir, as shown in Fig. 2. The 8.9 MW project was developed by NJR Clean Energy Ventures to power a water-treatment plant.

A recent study showed the maximum technical potential capacity of FPVs on the CONUS reservoirs to be between 861 GW_{DC} and 1,042 GW_{DC} [13], [14]. In this analysis, 847 reservoirs managed by the Federal Energy Regulatory Commission, the United States Army Corps of

Engineers (USACE), and the United States Bureau of Reclamation were analyzed based on their bathymetry, reservoir purpose, and such environmental conditions as snow loading, wind speeds, and water velocities. Additionally, it was estimated that FPV could reduce 14% of evaporation (gallons/year), on average, with a maximum of 40% reduction in the Salton Sea Reservoir, where the estimates found that a coverage of 81% of the water body could yield approximately 76 GW_{DC} of capacity.

When considering the hybridization of FPV with other sources of renewable energy, hydropower is the first candidate due to immediate co-benefits. Hydropower plants have existing infrastructure that can be repurposed by FPV, reducing shared capital, operation, and maintenance cost. The hybridized FPV-hydro can also help reduce the potential disturbances to frequency and speed regulators caused by highly variable solar power generation [15]. For existing hydropower plants, FPVs add to the flexibility of hydroelectric power, conserving water resources and ensuring a reliable supply for urban and agricultural irrigation needs [16]. FPV can further improve the level of dissolved oxygen and reduce evaporation.

Few studies have explored the complementary operation of FPV-hydro systems. To flourish water-food-energy nexus synergies, Zhou et al. [17] developed a grasshopper algorithm-based multi-objective optimization model to maximize simultaneously the generation of an FPV-hydro system, the ratio of water storage to reservoir capacity, and the ratio of water supply to water demand. Liu et al. [18] proposed a coordinated operation model for a FPV and pumped-storage power system, leveraging a generic algorithm (GA) to optimize electricity generation while minimizing energy imbalance.

By regulating a set of variable parameters, an optimization process maximizes or minimizes one or more objectives without violating design constraints [19]. In addition to optimizing hybridized standalone plants, studies such as [2], [7], and [20] have explored the optimal complementary generation of a series of VRE plants. Nevertheless, there is a lack of studies investigating the recommended nameplate capacity of VRE plants while optimizing complementarity metrics within the constraints of available resources.

Based on potential FPV resources in the CONUS, this paper analyzes the complementarity of theoretical FPV plants co-located with existing hydropower plants. First, the expected generation from each source is estimated using available flow measurements and irradiance data. Next, heuristic optimization is applied to determine the optimal FPV capacity for the analyzed reservoirs by maximizing its complementarity with hydropower generation. Finally, insights into complementarity are provided to support the siting and resource adequacy analysis of FPV-hydro hybrid power plants. The main contribution of this paper can be summarized as follows:

- This complementarity analysis identifies specific locations across the CONUS where integrating an FPV farm

with an existing hydropower plant could enhance hybrid plant generation.

- We further refine the technical potential of FPV in CONUS by determining the optimal FPV nameplate capacity using a heuristic optimization algorithm for selected sites, where integrating FPV with existing hydropower plants will result in a hybrid plant with reduced variability.

The rest of this paper is organized as follows: Section II elaborates on the methods used to pair FPVs with EHAs and the calculation of their respective generation profiles. Section III presents the complementarity metrics and optimization methodology. Section IV follows with the optimization results and corresponding complementarity analysis, and Section V concludes the paper.

II. GENERATION PROFILE PREPARATION

As shown in Fig. 3, the preparation of FPV- and hydropower-generation profiles includes the following three steps, where couples of databases and Python libraries used are further introduced in the rest of this section.

- 1) Determine the reservoirs that have an operating hydropower plant, potential for FPV based on the resource assessment conducted by [13], and an associated United States Geological Survey (USGS) stream gauge.
- 2) Retrieve USGS discharge data from the USGS Water Services [21], and determine the analyzed years with maximum available data points for each site.
- 3) Calculate the generation profiles of FPVs and hydropower with pvlib [22] and HydroGenerate [23].

A. DETERMINATION OF ANALYZED SITES AND YEARS

The AquaPV toolkit [24] provides foundational data and analysis for policymakers, developers, and other stakeholders seeking to understand FPV-project viability on the U.S. reservoirs [13].

The theoretical co-location of hydropower and potential FPV reservoirs is determined by finding the plants (FPV and hydropower) with shared U.S. Energy Information Administration (EIA) Plant ID from both the AquaPV technical potential and HydroSource's EHA Capacity Plant Database (2005–2023) [25]. The EIA Plant ID is an identifier that the EIA uses to track power plants. The HydroSource data platform provides up-to-date information and reliable technical and analytical support for hydropower generation and water management in the U.S. [26]. Dataset [25] summarizes key characteristics of operational U.S. pumped-storage and hybrid plants with 1 megawatt or greater of nameplate capacity.

The USGS is the scientific agency, providing critical data and expertise on earth, water, biology, and mapping to support informed decision-making on environmental and public safety issues [27]. Because discharge measurement is necessary to estimate hydropower generation, the population of

sites is further reduced by finding those with an associated USGS stream gauge. With these requirements in place, the EHA Plant ID is used to merge site information from USGS gauges [25]. After some outlier sites are eliminated, 39 analyzed co-located FPV-EHA reservoirs are determined.

As illustrated in Fig. 3, 10 years (2014–2023) of discharge measurements for 39 sites are retrieved from USGS instantaneous values service. However, as expected with field measurements, not all of the data retrieved are complete or of good quality. Therefore, only timestamps with “A” quality code—meaning that the records are approved for publication—are considered in this paper [28]. After resampling the datasets from 15-minute sampling frequency to hourly, the analyzed years are determined with the most (maximum) available good-quality discharge data. As a result, the analyzed years, as shown in Fig. 4, are different from site to site, ranging from 1 to 8 years. Thirty-one of 39 sites have at least one full year profile, and the minimum number of data points in the profiles is 8,024, which covers more than 90% of the hours of a year (8,760 hours).

Fig. 5 illustrates a capacity comparison of FPV potential, existing hydropower plant, and optimal FPV capacity of each site. The figure lists the hydroelectric plant names of analyzed reservoirs.

B. SYNTHETIC GENERATION PROFILES

Pvlib [22] and HydroGenerate [23] are the two main open-source tools that were used to estimate the FPV and EHA generation profiles, respectively. Pvlib python is an open-source toolbox that provides over 100 empirical and physical models for simulations ranging from PV energy components to overall weather-to-power system. Leveraging pvlib iotools [29] for access to solar-resource data from PVGIS ERA5 [30], a 1-MW FPV system-generation profile for analyzed sites is estimated under identically representative configurations, as shown in Table 1. The generation values in MW units can also be regarded as capacity factors. With respect to hydropower, HydroGenerate is used to estimate hydropower generation based on discharge flow and hydraulic head. HydroGenerate determines the turbine type based on hydraulic head and design flow, with the latter calculated as the 70th percentile of the flow range at that location. While the discharge-flow time series is obtained from USGS, the hydraulic head is calculated separately. This is further discussed in Subsection II-C.

C. HEAD CALCULATION

Hydraulic head can be calculated by subtracting the vertical difference between the reservoir elevation in the forebay and the elevation of the tailwater where the water is discharged. Hydraulic head can vary throughout the year, especially in systems with significant seasonal reservoir drawdown. Several publicly available datasets describe historical reservoir elevations, including ResOpsUS [31] (for large dams in the CONUS) and the Database for Hydrological Time Series of

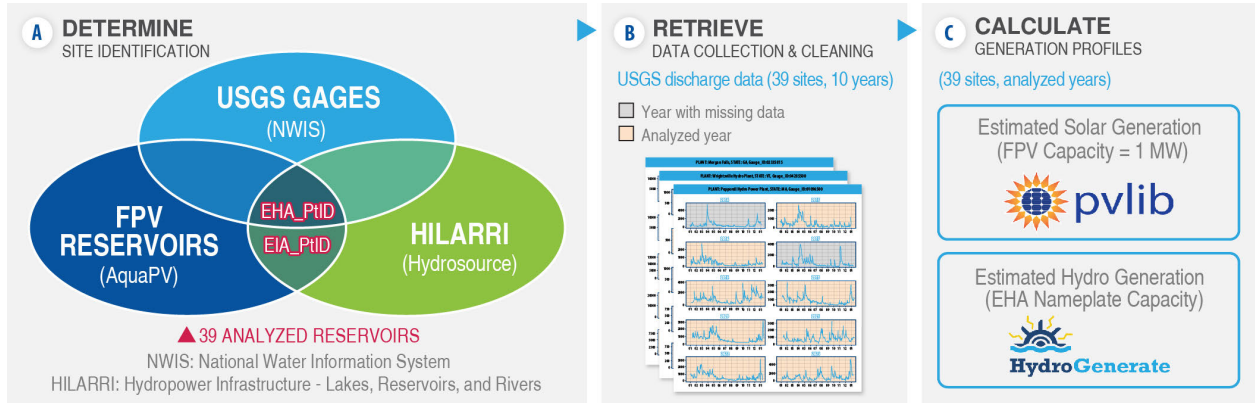


FIGURE 3. Workflow of producing FPV and EHA generation profile.

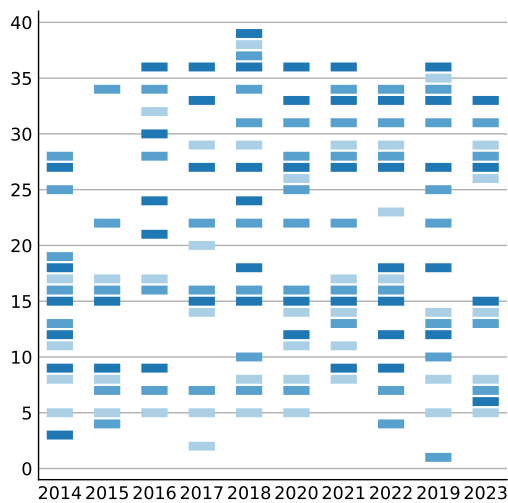


FIGURE 4. Years analyzed for 39 locations. Blue boxes mark the analyzed years of each site. The graph uses multiple shades of blue to clearly separate each row. For example, the analyzed year for Site 1 is 2019, whereas the analyzed periods for Site 5 are 2014–2020 and 2019–2023.

Inland Waters (DAHITI). However, most dams (hydropower or non-powered) do not have long-term historical reservoir elevation records. To develop a proxy for the seasonal fluctuations in hydraulic head, we looked to dams with available historical time-series data and information describing the primary operating purpose and dam height, which are widely available for most dams in the U.S. through the National Inventory of Dams (NID) [32]. First, hydraulic-head data were obtained for those dams included in the USACE detailed assessment of development feasibility [33]. Then, head was approximated at dams with elevation records in ResOpsUS or DAHITI by retrieving downstream elevations from 1- and 10-m-resolution elevation data [34]. Assuming minimal changes in tailwater elevations, the daily historical hydraulic head was calculated as the difference between reservoir and tailwater elevations. Once approximate (or reported) hydraulic heads were calculated, these data points were

TABLE 1. Representative FPV system configurations.

Attributes	Value	Unit
System capacity	1	MW
DC to AC ratio	1.3	\
Tilt angle [37]	11	degrees
System efficiency	90	%
Azimuth angle	180	degrees from the north

aggregated to median monthly values and then scaled relative to the height reported in the NID. This resulted in hydraulic head expressed as a fraction of the NID height for each month from January to December. Then, monthly relative hydraulic-height scaling factors were calculated as the median value for each purpose (fish and wildlife pond, flood control, irrigation, navigation, recreation, or water supply). Once these scaling factors were calculated, they were applied to each of the dams that did not have historical reservoir elevations, according to their reported primary purpose and NID height. This process is summarized in Fig. 6. The average hydraulic head for the whole year is input as the head parameter to HydroGenerate.

III. COMPLEMENTARITY METRICS AND OPTIMIZATION METHOD

In this section, we will discuss the evaluated metrics for complementarity analysis and the optimization methodology in this study.

A. COMPLEMENTARITY METRICS

To analyze the complementary relationship of each hydropower plant and FPV pair, we leverage Pearson correlation coefficient, ρ , and stability coefficient, C_{stab} . As the most commonly applied metric for complementarity analysis, the linear correlation between the generation time series of hydropower and FPVs can be measured using the Pearson coefficient [36]. However, in addition to the linear relationship for co-located plants, the plant operators could consider the hybrid generation of the complementary system. In other

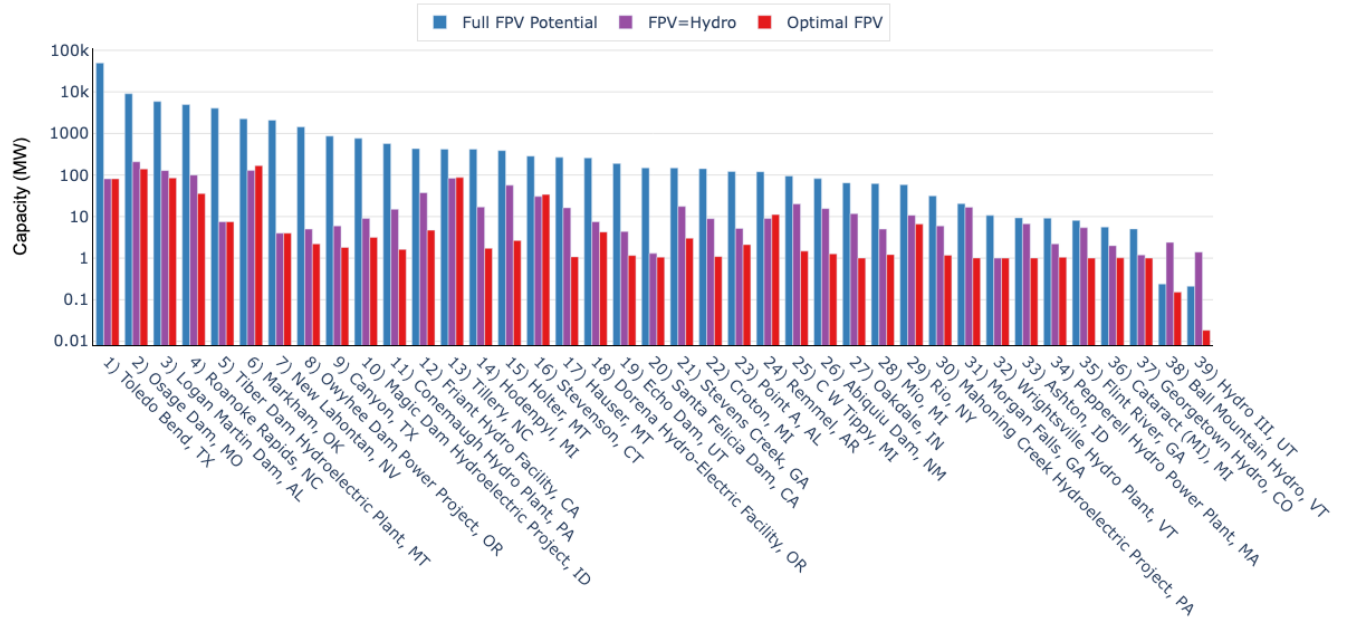


FIGURE 5. All 39 locations capacity for full FPV potential, hydropower plant, and optimized FPV.

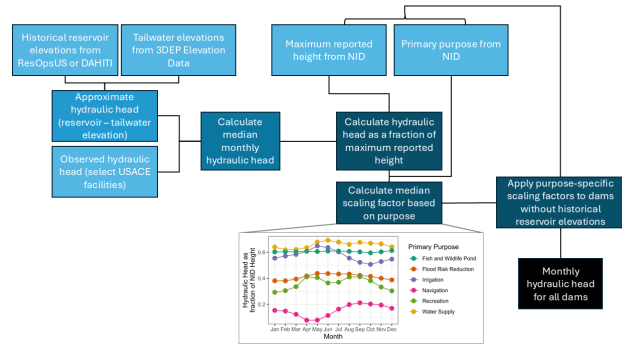


FIGURE 6. The process to determine the head at the EHAs.

words, the Pearson coefficient values remain the same with generation profiles $\{x, y\}$ and $\{x, 2y\}$, where x and y , in the unit of MW, denote time-series generation of power compared, and $\{x, 2y\}$ profile would be more preferable as it doubles the generation of the second type of power.

Sterl et al. [12] proposed the stability coefficient specifically for complementarity analysis accounting for hybrid generation. The mathematical definition of the daily stability coefficient can be found in (1):

$$C_{\text{stab, day}} = 1 - \frac{\sqrt{\sum_{\text{day}} (CF_{\text{mix}}(t) - \overline{CF_{\text{mix}}})^2} \overline{CF_{\text{base}}}}{\sqrt{\sum_{\text{day}} (CF_{\text{base}}(t) - \overline{CF_{\text{base}}})^2} \overline{CF_{\text{mix}}}} \quad (1)$$

where CF_{base} and CF_{mix} represent the capacity factor of the base resource and the hybrid generation, respectively. $\overline{CF}$ denotes a daily average capacity factor; t iterates the time

step within a day. In our case, the overall stability coefficient, C_{stab} , of each site is calculated through the average of $C_{\text{stab, day}}$ for all analyzed years. Instead of hydropower, however, we consider solar energy as the base resource. While the variability of hydropower hinges on the nature of the flow rate of the river and the design of the dam, the diurnal characteristic of solar energy leads to a prototype profile of solar generation in a day; that is, power is only generated in the daytime. Therefore, if we consider hydropower generation as the base, the daily stability coefficient would tend to be negatively infinite when the river is frozen or dry. By contrast, if FPV generation is regarded as the base, the variance fraction would be 1 in the same case, and the stability coefficient only depends on capacity-factor improvement. The CF_{mix} is calculated as $CF_{\text{mix}} = (mCF_{\text{EHA}} + nCF_{\text{FPV}})/(m + n)$, where m and n are the nameplate capacity of the EHA and FPV, respectively.

According to (1), after the addition of the complementary resource, the lower variance and the higher capacity factor contribute to the higher stability coefficient value. Further illustration of how the inputs affect the stability coefficient values is provided in [12].

By definition, $C_{\text{stab}} \leq 1$, with $C_{\text{stab}} = 0$ means that there is no improvement in balancing the generation with the addition of hydropower generation, and $C_{\text{stab}} = 1$ means that the hybrid generation completely removes the variability of the base resource [4], [12]. The Pearson coefficient ranges from -1 to 1 . While $\rho = -1$ indicates perfect complementarity, $\rho = 1$ represents perfect synchrony or lack of complementarity, and $\rho = 0$ means no correlation of the two resources.

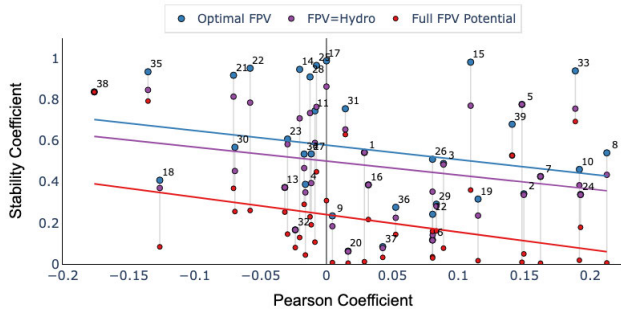


FIGURE 7. Correlation of stability coefficient and Pearson coefficient. Linear regressions of stability coefficient to Pearson coefficient are provided. Different stability coefficient values with variable FPV capacity of the same site are connected by vertical lines. The numbers beside the blue points are the number of each site.

Fig. 7 illustrates the correlation of the stability coefficient and Pearson coefficient. It is notable that, for capacity $FPV=hydro$ case, when $P_{FPV} \leq m$, the $n = P_{FPV}$ would be input to calculate C_{stab} instead of $n = m$, where P_{FPV} denotes the potential capacity of FPV. The Pearson coefficient value remains the same when only the net generation of FPV changes with different capacity. The linear-regression lines show that the sites with lower Pearson coefficient values tend to have a higher stability coefficient, which indicates they generally give similar conclusions for complementarity analysis. However, because of the hybrid-generation consideration, the stability coefficient can be further optimized by adjusting the FPV capacity.

B. OPTIMIZATION METHODOLOGY

In previous sections, we introduced the concept of complementarity. Previous research, [4] and [12], assessed the complementarity of resource pairs by assuming an equal megawatt capacity for the two plants. However, this can be quite limiting given that some hydropower owners might be interested in adding FPV so their generation more resembles a base-load plant (i.e., with a greater stability coefficient over time).

This subsection explores the optimization of FPV capacity that would yield the most stable generation in the hybrid plant. As illustrated in (2), the objective is to maximize C_{stab} by optimizing FPV capacity. The maximum optimal FPV capacity is limited to each reservoir's potential capacity while the minimum is set at 1 MW to align with large-scale solar capacity. For two locations with less than 1 MW potential, the minimum capacity is set to 0.

$$\begin{aligned} & \max_n C_{stab}(m, n, CF_{FPV}, CF_{EHA}) \\ & \text{subject to} \\ & 1 \leq n \leq P_{FPV}, \text{ if } P_{FPV} > 1 \\ & 0 \leq n \leq P_{FPV}, \text{ if } P_{FPV} \leq 1 \end{aligned} \quad (2)$$

As mentioned in the previous section, $C_{stab} = 1/d * \sum_{i=1}^d C_{stab,day}$, where d is the number of the days in the

analyzed years. Therefore, the optimization process is based on the available historical profiles, which vary from site to site. And it further implies that the optimization process doesn't consider the dynamic hydropower operation outside the profiles.

The GA is adopted to solve the optimization problem in this study [19]. This is a popular heuristic optimization method, which mimics the process of natural selection to explore a vast search space and identify optimal or near-optimal solutions. The main reason to select GA is that the objective function is non-linear and non-convex, which is not differentiable; therefore, traditional gradient-based methods are not applicable. Moreover, there is a large search space to find the globally optimal coefficient, and GA allows for parallel searching and faster convergence relative to other sequential-optimization methods [37]. More importantly, GA can incorporate domain-specific knowledge through the crossover and mutation operators that improve the efficiency of the search process. In this study, based on our domain knowledge, the population size is set to 50. The parent portion in the population is 0.3, with 0.5 and 0.2 crossover and mutation probability, respectively. To avoid local optima, the algorithm is terminated after 50 generations instead of relying on a convergence criterion. One percent elites are kept at every generation.

As a heuristic evolutionary algorithm, however, GA has no proof of convergence to an optimal solution [19]. Therefore, the optimal FPV capacity is generated in this study as the best of three values: the optimal solution from applying the GA method, the EHA capacity (where $m < P_{FPV}$), or the full potential FPV capacity, which contributes to the maximum C_{stab} value.

IV. COMPLEMENTARY ANALYSIS BASED ON OPTIMIZATION RESULTS

This section presents the optimal results obtained by the GA, followed by a complementarity analysis based on these results. Because most research analyzed the complementarity of two renewable energies with a 1:1 nameplate capacity ratio, we regard the metric values with capacity $FPV_{MW} = Hydro_{MW}$ as the first benchmark. Another benchmark comes from FPV capacity equal to full potential FPV capacity in the analyzed reservoirs. All numerical results are summarized in Table 2, including FPV and hydropower capacity, stability coefficient values, and Pearson coefficient values.

A. OPTIMAL RESULTS

Fig. 8 illustrates the optimization results compared with benchmarks. From the capacity comparison axis, we can see that even though numerous reservoirs have a large potential FPV resource, they are partially complementary with hydropower generation.

After optimization, more than half of the analyzed reservoirs achieve a stability coefficient above 0.5, with a median value of 0.54. In comparison, the median stability values for equal FPV and hydro capacities and for full FPV capacity

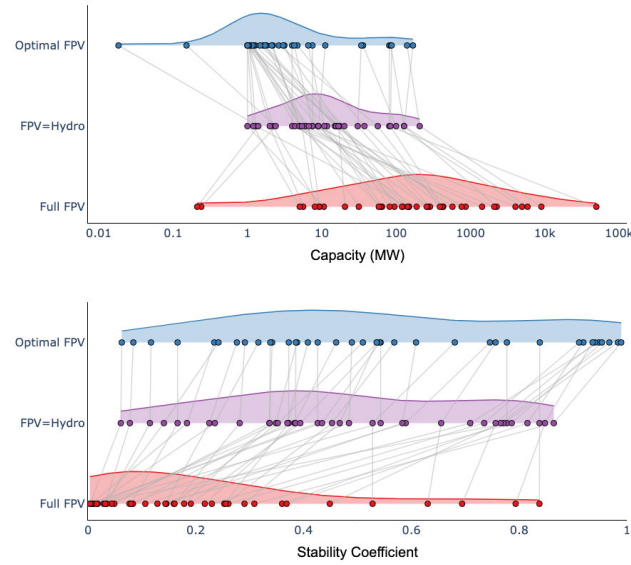


FIGURE 8. Optimization performance comparison. (a) The top axis compares the capacity among existing hydropower plants, optimal FPV and potential FPV. Because of the large range of potential FPV capacity, the x axis is in logarithmic scale. (b) The bottom axis compares the stability coefficient with different FPV capacity as input: FPV=hydro, optimal FPV, and full FPV capacity. Points of the same site are connected by the grey lines. The half violin plots show the distribution of data points.

are 0.43 and 0.15, respectively. The averaged stability coefficient values for full FPV potential capacity, same FPV and hydropower capacity, and optimal FPV capacity are 0.21, 0.48, and 0.55, respectively. The averaged increase from the minimum stability coefficient value to the optimal one of each site is 0.34, with a median of 0.31. The maximum improvement is 0.82, from value 0.13 to 0.95, obtained from Site 14, Hodenpy1, in Michigan. The potential FPV capacity of Site 14 is 418.62 MW, and the optimal FPV capacity obtained by GA is 1.72 MW, at which the nameplate capacity of existing hydropower plant is 17 MW.

Fig. 9 illustrates the net generation comparison of optimal theoretical FPV, estimating hydropower and hybridized generation at either a 1:1 ratio of FPV to hydro capacity or optimal FPV capacity for Site 14. Fig. 9 (a) shows the improvement of complementarity from capacity FPV = hydro to optimal FPV capacity for coordinated operation, where the purple curve is less variable than the red one. Because the potential FPV capacity is 418.62 MW, with which the hybridization would be more variable (larger variance) than FPV = hydro case, the related curves are omitted.

B. COMPLEMENTARITY ANALYSIS WITH OPTIMIZATION RESULTS

The complementarity analysis in this subsection is mainly based on the Figs. 10 and 11, and Table 2. Specifically, Fig. 10 compares the complementary metric values of the sites analyzed on a daily, monthly, and yearly basis. All values are calculated based on optimal FPV-capacity results. One should

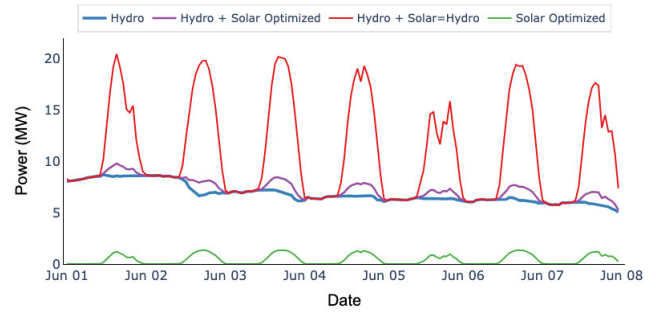


FIGURE 9. Generated power comparison of existing hydropower (in blue), optimal FPV (in green), and hydro and FPV hybridization (in purple when FPV capacity is optimized, and in red when FPV capacity equals to hydropower) from June 1, 2020, through June 7, 2020, of Site 14.

note that because the analyzed years of each site differ, the wider spread does not mean a more-variable complementarity relationship. Fig. 11 further showcases the locations of the analyzed sites and the differences in the aggregated stability coefficient with different FPV nameplate capacities as input.

1) ANALYSIS BASED ON PEARSON CORRELATION COEFFICIENT

Similar to the conclusion from [4], the Pearson coefficient values in many reservoirs across the U.S. are near 0 for annual and monthly averages, indicating that the generation of FPVs and hydropower is neither linearly correlated nor asynchronous when evaluated at these scales. As the daily Pearson coefficient values of most (except Sites 17, 20 and 37) of analyzed sites range from lower than -0.5 to higher than 0.5 , all of the median daily coefficient numbers are either lower than 0 (27 sites) or equal to 0 (12 sites). Because -1 represents a perfect anti-correlation in the Pearson coefficient, this observation suggests that FPV and existing hydropower plants in 69.23% of the analyzed reservoirs are statistically complementary for more than half the days in a year. The reservoirs with relatively strong complementarity based on an aggregated yearly Pearson coefficient are Site 38 in Vermont, Site 35 in Georgia, and Site 18 in Oregon.

Interestingly, the daily, monthly, and yearly Pearson coefficient values are all 0 for Site 17. That is because the Hauser hydroelectric plant at Site 17 has been running at full capacity, with a discharge flow higher than 2500 cfs for the past 10 years, including the analyzed years {2014, 2015, 2016, 2021, 2022}. One should note that this flat generation is estimated by HydroGenerate. The capacity factor of the Hauser plant ranged from 73 to 105% over the last 10 years, as recorded in the database [38] from Hydrosources. Its stability coefficient based performance is discussed in Subsection IV-B.2.

2) ANALYSIS BASED ON STABILITY COEFFICIENT

Positive stability coefficient value means the addition of an existing hydropower plant helps balance the theoretical FPV generation. As shown in Fig. 11, all positive values of the sta-

TABLE 2. Numerical Summary of FPV capacity before and after optimization, existing hydropower capacity, comparative stability coefficient values, and Pearson Correlation coefficient values. One should note that the analyzed years of different sites differ. All the metric values may change based on another analyzed years.

Site	Potential FPV Capacity (MW)	Optimal FPV Capacity (MW)	Hydropower Capacity (MW)	Stability Coefficient (Optimal)	Stability Coefficient (FPV = Hydro)	Stability Coefficient (Full FPV Potential)	Pearson Coefficient
1	49528.27	81.0	81.0	0.54	0.54	0.01	0.03
2	9012.61	140.55	208.0	0.34	0.34	0.05	0.15
3	5875.12	84.93	128.1	0.49	0.48	0.08	0.09
4	4947.11	36.0	100.0	0.39	0.35	0.04	-0.02
5	4042.23	7.5	7.5	0.78	0.78	0.01	0.15
6	2258.44	168.66	128.4	0.12	0.11	0.04	0.08
7	2091.17	4.0	4.0	0.43	0.43	0.0	0.16
8	1436.1	2.2	5.0	0.54	0.43	0.01	0.21
9	863.38	1.81	6.0	0.23	0.18	0.01	0.0
10	762.09	3.14	9.0	0.46	0.38	0.02	0.19
11	573.35	1.63	15.0	0.75	0.59	0.11	-0.01
12	430.9	4.7	37.5	0.24	0.14	0.03	0.08
13	421.39	87.23	84.0	0.37	0.37	0.25	-0.03
14	418.62	1.72	17.0	0.95	0.71	0.13	-0.02
15	388.04	2.65	56.8	0.98	0.77	0.36	0.11
16	285.89	33.96	30.5	0.39	0.39	0.22	0.03
17	265.5	1.08	16.3	0.99	0.86	0.31	0.0
18	257.77	4.27	7.5	0.41	0.37	0.08	-0.13
19	189.12	1.16	4.4	0.32	0.24	0.02	0.11
20	149.38	1.06	1.3	0.06	0.06	0.0	0.02
21	148.02	3.02	17.6	0.92	0.82	0.37	-0.07
22	142.2	1.09	8.9	0.95	0.79	0.26	-0.06
23	122.33	2.12	5.2	0.61	0.58	0.15	-0.03
24	120.1	11.15	9.0	0.34	0.34	0.18	0.19
25	95.1	1.48	20.1	0.97	0.77	0.45	-0.01
26	82.03	1.28	15.6	0.51	0.35	0.16	0.08
27	64.91	1.0	11.8	0.54	0.39	0.19	-0.01
28	62.16	1.22	5.0	0.91	0.74	0.23	-0.01
29	58.44	6.59	10.8	0.29	0.28	0.16	0.08
30	31.51	1.17	6.0	0.57	0.45	0.26	-0.07
31	20.55	1.01	16.8	0.76	0.66	0.63	0.01
32	10.69	1.0	1.0	0.17	0.17	0.08	-0.02
33	9.33	1.0	6.7	0.94	0.76	0.69	0.19
34	9.19	1.05	2.2	0.54	0.47	0.29	-0.02
35	8.09	1.0	5.4	0.94	0.85	0.79	-0.14
36	5.63	1.02	2.0	0.28	0.23	0.14	0.05
37	5.05	1.0	1.2	0.08	0.08	0.03	0.04
38	0.24	0.15	2.4	0.84	0.84	0.84	-0.18
39	0.21	0.02	1.4	0.68	0.53	0.53	0.14

bility coefficient, even before the optimization, prove that the variance of FPV generation alone is removed more or less by hybridization with hydropower. This is also observed in [4]. Fig. 10 further illustrates that, with optimal FPV capacity, the lowest first-quartile value of the daily stability coefficient is 0 for the analyzed reservoirs, all median monthly stability coefficient values are positive, and 21 out of 39 sites' median yearly values are over 0.5. This confirms the feasibility of FPV-hydro complementary operation.

It is worth noting that the stability coefficient can be negative at some sites over certain periods, as shown in Fig. 10. This primarily occurs in daily complementary scenarios and may suggest that hybridization renders the system less stable under specific conditions of that day. As detailed in information published by IEA [1], the stability coefficient quantifies the extent to which the capacity factor deviates from its average, relative to baseline deviations from average. If the capacity factor after hybridization is significantly lower

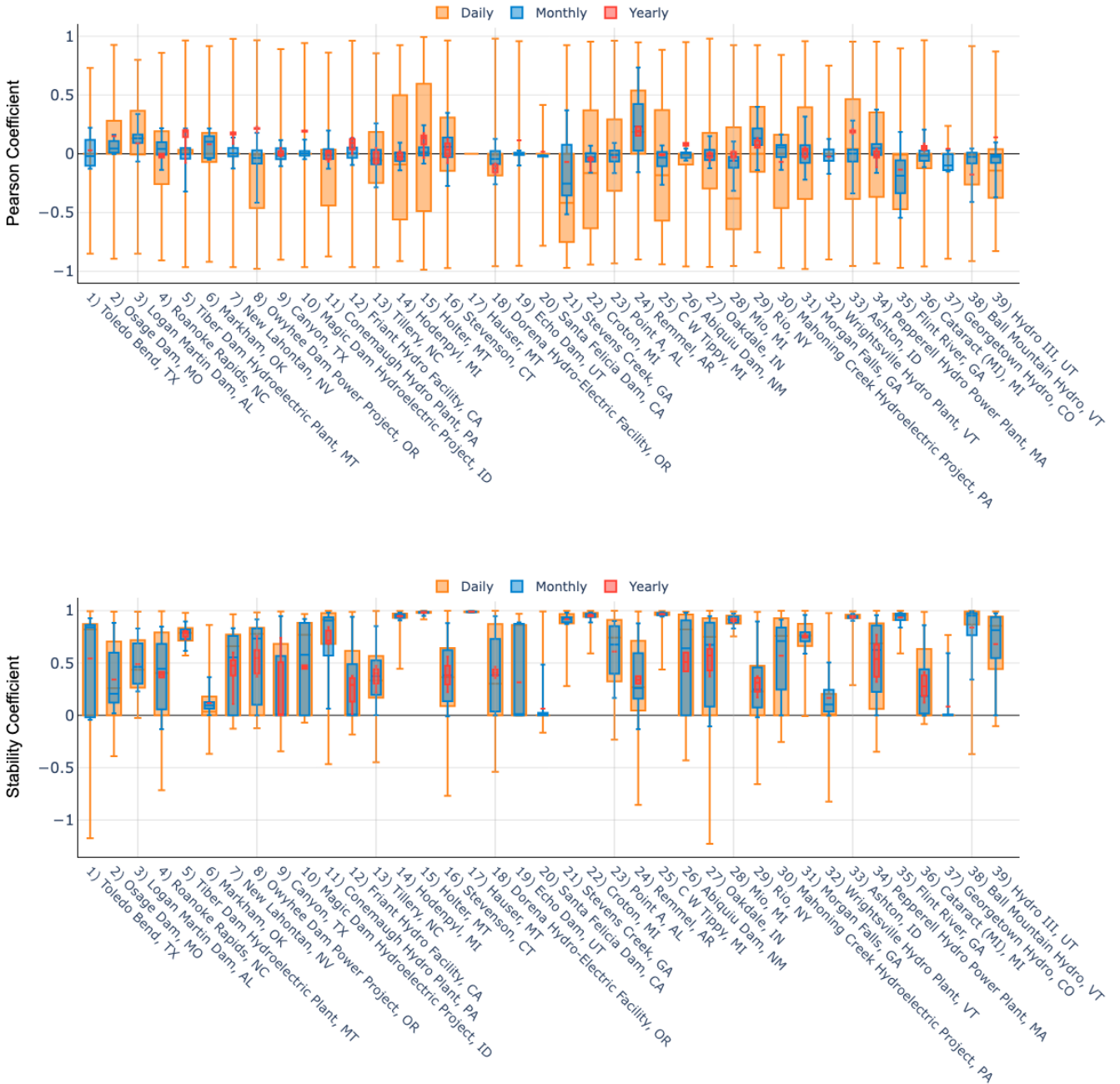


FIGURE 10. Daily, monthly, and yearly complementarity metrics of analyzed locations. All values are based on optimal FPV-capacity results. Because the analyzed years vary across sites, a wider spread does not necessarily indicate a more variable correlation.

than before, the mean ratio increases, potentially leading to a negative stability coefficient. Additionally, an increase in variability could result in negative values. However, due to the smoothing effect, occurrences of negative stability coefficients are much less frequent on monthly and yearly scales.

For the site 17, with no linear correlation between existing hydropower plant and FPV as indicated by Pearson coefficient, after optimization, its optimal stability coefficient

achieves 0.99, from 0.31 (based on full FPV potential) and 0.86 (with capacity FPV = hydro). The optimal FPV capacity is 1.08 MW, which is close to the lower bound of the FPV capacity. This optimal capacity is also because of the flat hydropower generation. While the addition of existing hydropower does not reduce the variability of standalone FPV plant, the optimization algorithm would reduce the FPV nameplate capacity in order to improve the stability coefficient value by increasing the ratio of hybrid (FPV+EHA) to

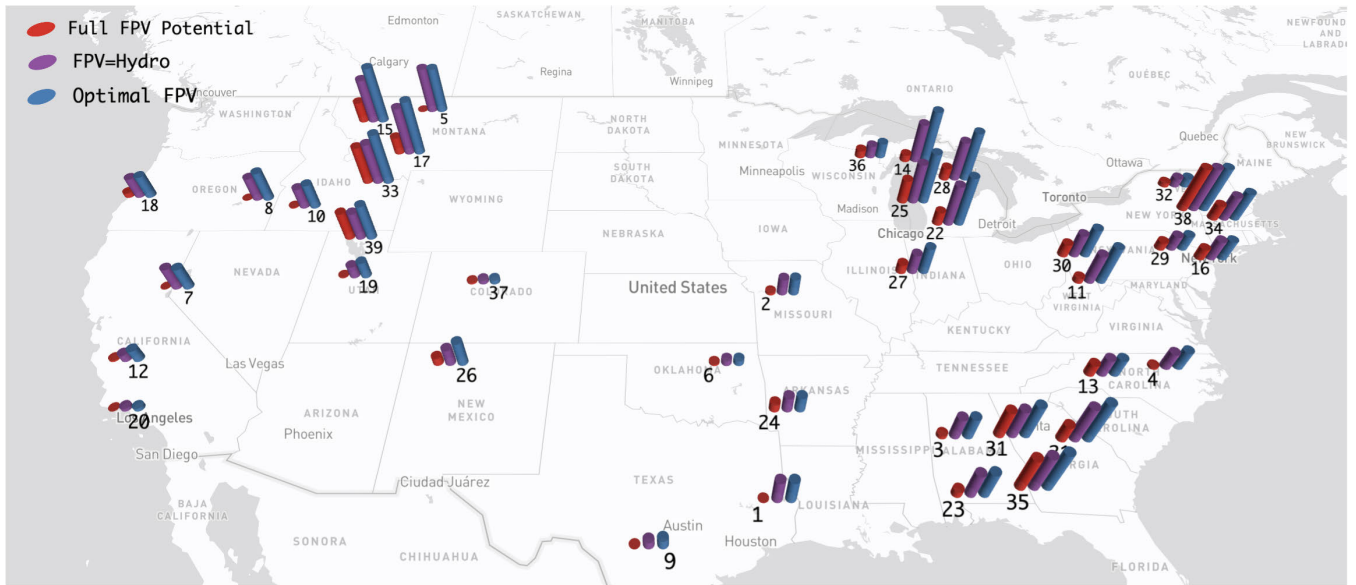


FIGURE 11. The differences in the stability coefficients for each location. Note that the shortest bar represents a value of ~ 0.0035 , and the tallest bar's value is ~ 0.9895 .

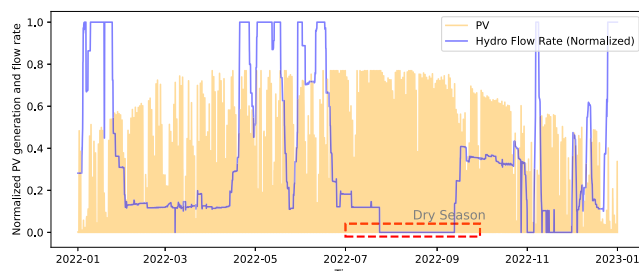


FIGURE 12. PV generation and flow-rate time-series plot for Site 18.

base energy (FPV) generation. Fig. 7 illustrates the change in stability coefficient across different FPV capacities.

3) HIGH COMPATIBILITY SITES

As shown in Fig. 11, for Sites 35 and 38 with low Pearson coefficient, the optimal stability coefficient values are also higher than 0.8. However, the optimal stability coefficient of Site 18, which has the third lowest Pearson coefficient value, -0.13 , is around 0.4. This is because the flow rate at Site 18 during summer is nearly zero or completely dry, which is illustrated in Fig. 12. This results in the overall low stability coefficient. The difference of the stability coefficient for the three sites can be also found in Fig. 7.

Four of the sites—Sites 15, 17, 22, and 25—in Montana and Michigan, achieve more than 0.95 stability coefficient after optimization. Sites 14, 21, 28, 33, and 35 follow with a greater than 0.90 stability coefficient. Nevertheless, only Site 14, in Michigan, Site 15 in Montana, and Site 21 in Georgia have an optimal FPV nameplate capacity larger than 1.5 MW. The optimal capacities are 1.72, 2.65, and 3.02 MW for

Sites 14, 15, and 21, respectively. If we use the FPV = hydro capacity as input, the aggregated stability coefficient values of these nine sites are already over 0.7. Therefore, further consideration between productivity and complementarity is needed.

4) LARGE OPTIMAL CAPACITY SITES

While 20% of analyzed reservoirs possess more than 1,000 MW potential FPV capacity, the largest optimal capacity is 168.66 MW in the case study, which is achieved by Site 6 in Oklahoma, with 128.4 MW hydropower capacity. Sites 2 in Missouri, Site 13 in North Carolina, and Site 3 in Alabama follow, with 140.55, 87.23, and 84.93 MW optimal FPV capacity, respectively, and 208, 84, and 128.1 MW hydropower capacity, respectively. Located in Texas, Site 1, which has the highest potential FPV capacity, ranks fifth with 81 MW optimal FPV capacity with the same capacity hydropower.

V. CONCLUSION

This paper investigates the complementarity of existing hydropower assets and potential FPV across the CONUS. A total of 39 reservoirs were analyzed, based on criteria that each reservoir possess an existing hydropower plant, suitability for potential FPV, and an associated USGS gauge for discharge measurement. Analyzed years are different from site to site, depending on the quality of the discharge measurement. The Pearson correlation coefficient and stability coefficient are evaluated for hydropower-FPV complementarity. Regarding FPV potential, the technical potential values from AquaPV are set as the constraint, and an optimization problem is defined to obtain the highest stability coefficient using the GA.

The averaged stability coefficient increment with optimization is 0.34, where all original stability coefficient values are between 0 and 1. After optimization, the analyzed sites with more than 0.95 optimized stability coefficient values include existing plants Hauser and Holter in Montana, as well as plants C. W. Tippy and Croton in Michigan. This analysis will assist such stakeholders as hydropower owner/operators and solar developers in future FPV site planning that considers complementarity with hydropower.

Future work will include the complementarity analysis considering the following factors 1) seasonal dynamics in existing hydropower plants and FPV; and 2) techno-economic considerations that include location-based incentives, costs, and electricity prices. Additional analysis could include 1) balance of plant and dispatch optimization of hydropower and FPV generation to serve local needs; and 2) regulatory or policy framework influences on FPV deployments.

ACKNOWLEDGMENT

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