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Evaluating the Economic Feasibility of Utility-Scale Hybrid Power Plants Under Divergent Policy Environments: A Multi-Objective Approach

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Abstract

This study presents a novel policy-integrated optimization framework for utility-scale hybrid power plants (HPP), including wind–solar–battery, addressing a critical gap in hybrid renewable energy system design by simultaneously evaluating technical, operational, and economic performance under dynamic policy environments. Unlike conventional approaches that treat these factors separately, this multi-objective optimization model uniquely combines (1) technical reliability assessment through Loss of Load Probability (LOLP) metrics, (2) operational efficiency analysis via curtailment minimization, and (3) economic viability evaluation using net present value (NPV) optimization—all while accounting for policy incentive structures. Applying this framework to comparative U.S. and India case studies reveals how tailored policy combinations can enhance project viability compared to single-incentive scenarios. The results indicate that HPPs are financially unviable without policy support, but targeted incentives like Investment Tax Credits (ITCs) and Production Tax Credits (PTCs) in the U.S. and Accelerated Depreciation (AD), Generation-Based Incentives (GBIs), and Viability Gap Funding (VGF) can improve their viability. The U.S. scenario sees a 197% increase in NPV and a reduction in LCOE to USD 0.055/kWh, while India achieves a 107% turnaround in NPV and an LCOE of USD 0.039/kWh. Sensitivity and breakeven analyses reveal that interest rates and consistent policy support are critical, especially in emerging markets. Specific policy thresholds are identified for feasibility, providing actionable benchmarks. By bridging the gap between technical optimization and policy analysis, this work provides both a methodological advance for HPP design and practical insights for policymakers seeking to accelerate HPP. While this study centers on incentive-driven feasibility, it also outlines key modeling limitations and future improvements, such as market participation, environmental constraints, and advanced system design that will support future HPP planning.

Keywords: hybrid power plant; techno-economic optimization; policy incentives; multi-objective particle swarm optimization; energy policy; incentives

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1. Introduction

The global energy transition requires innovative solutions to integrate high shares of variable renewable energy while maintaining grid reliability. Hybrid power plants (HPPs) that combine wind, solar, and battery storage have emerged as a technically viable pathway, offering higher capacity factors, optimal infrastructure utilization, enhanced grid flexibility, minimal land requirements, and dispatchable electricity with lower curtailment than standalone projects [1–8]. However, large-scale deployment of HPPs faces challenges, including high upfront capital costs, uncertain long-term revenue streams, and fragmented regulatory frameworks, particularly in emerging markets [1,3,7]. Table S1 of the Supplementary Materials provides detailed policy mapping and global incentive structures relevant to HPP deployment.

The growing prominence of HPPs has spurred significant research into their techno-economic optimization. Previous studies can be broadly categorized based on their primary focus: optimal sizing, techno-economic evaluation, and integrated policy and regulatory analysis [9].

A substantial work has focused on developing sophisticated algorithms for the optimal sizing of HPP components. Studies have employed various methods, such as Genetic Algorithms (GAs) for physical design in the U.S. [10], Multi-Objective Particle Swarm Optimization (MOPSO) for cost and reliability [11], and mixed integer linear programming (MILP) for component sizing and net present value (NPV) [12]. In Spain, González-Ramírez et al. [13] evaluated hybridization of existing wind farms with solar PV to maximize NPV improvements. Others, like León et al. [14] with the HyDesign tool, have focused on minimizing the Levelized Cost of Energy (LCOE) and NPV in India. While these studies provide a strong foundation in algorithmic design, they often operate in a policy-agnostic environment, treating financial and technical parameters as static inputs.

Concurrently, other researchers have examined the critical role of policy and regulation. Gorman et al. [7] have extensively documented the status of hybrid plants and demonstrated how structured Power Purchase Agreements (PPAs) can enhance financial returns. Street and Prescott [15] assessed regulatory incentives in Brazil, though their analysis was primarily focused on network charges. Rocha et al. [16] evaluated regulatory frameworks for hybrids but did not integrate them with dynamic technical optimization. Silva and Estanqueiro [17] developed an MILP–GA framework to optimize the sizing and efficiency of wind–solar hybrid systems, incorporating feed-in tariff assumptions. While their approach contributes to the technical–economic optimization literature, it remains limited by its reliance on static policy incentives and its omission of reliability measures such as LOLP or curtailment. Grimaldi et al. [18] applied an MILP-based framework to optimize battery–wind integration, incorporating both battery degradation and wind curtailment. Their work advanced the field by explicitly modeling storage degradation, yet it remained limited to a static feed-in tariff regime. These studies highlight the importance of policy but often neglect the detailed technical integration and multi-objective trade-offs inherent in HPP operation.

A third category of studies has attempted to bridge the techno-economic and policy domains. For example, Bade et al. [9] and Giuffrida et al. [19] conducted techno-economic evaluations considering some policy incentives. However, these studies often treat policy inputs as static assumptions rather than dynamic, sensitive variables within the optimization loop. Furthermore, many existing frameworks suffer from a single-metric focus (e.g., maximizing NPV alone) or inadequate integration of reliability metrics like Loss of Load Probability (LOLP) with financial viability.

A comparative analysis of these approaches, summarized in Table 1, reveals three predominant limitations that this study seeks to address:

1. Single- or limited-metric focus, neglecting the multi-stakeholder priorities of investors (NPV), grid operators (LOLP), and policymakers (curtailment/efficiency).
2. Static or absent policy assumptions, failing to capture the dynamic and sensitive nature of real-world policy environments and their impact on bankability across different countries.
3. Inadequate integration of technical reliability constraints with financial viability assessments under divergent policy regimes.

Table 1. Comparative analysis of optimization approaches for utility-scale hybrid power plants, highlighting methods, objectives, policy considerations, and key limitations.

References	Method Used	Objectives	Policy Support	Key Limitations
[7]	HOPP	Max NPV	PPA	Lack of comprehensive analysis of policy
[9]	MOPSO, MOGA	Max NPV, min LOLP, and min curtailment	Partial	Lack of comprehensive policy inclusion
[10]	GA	Physical design and layout	No	Lack of technical–financial integration
[11]	MOPSO	Minimize average service cost and LPSP	No	Lack of comprehensive policy inclusion
[12]	MILP	Maximize NPV	No	Lacks technical and policy inclusion
[13]	MLR	Optimal size, Max NPV	No	Lack of comprehensive analysis, including policy
[14]	HyDesign	Minimize COE, maximize NPV	No	Exclude reliability and policy metrics; ignores forecasting uncertainty
[15]	-	Exploration of complementary, and renewable generation profiles	Network access charge (incentives)	Lack of comprehensive analysis
[16]	MO	Max NPV and min LCOE	No	Excluded technical analysis
[17]	MILP with GA	Optimal sizing, efficiency, and economic viability	FIT	Partial inclusion of static policy
[18]	HOMER Pro and REopt (commercial tools)	Evaluate NPV, NPC, LCOE, and payback	No	Single-objective, deterministic, limited to fixed profiles, and no policy inclusion
[19]	MILP	Max NPV, min curtailment, and battery degradation	FIT	Lacks detailed inclusion of economic and policy
[20]	GA and Iterative algorithm	Grid stability	No	Lack of comprehensive economic and policy inclusion
[21]	MCS	Sizing and loss of load expectation	No	Lacks financial integration and full technical analysis
[22]	HOPP (hybrid optimizer)	Spatially constrained hybrid sizing (e.g., Power-to-X systems)	No	Lacks comprehensive analysis
[23]	NSGA-II, CCP	Minimize system cost, reliability	No	Lack of policy inclusion
[Present study]	MOPSO	Max NPV, min LOLP, and min curtailment	Yes	-

MO: multi-objective; GA: Genetic Algorithm; NSGA: MLR: multi-level regression; MCS: Monte Carlo Simulation; non-dominated sorting genetic algorithm; HOPP: hybrid optimization and performance platform; HOMER: hybrid optimization of multiple energy resources; REopt: renewable energy integration and optimization; CCP: chance constrained programming; FIT: feed-in iariff.

This study addresses these limitations by developing a policy-integrated optimization framework for utility-scale wind–solar–battery hybrid systems. The primary objectives of this study are

- Construct a multi-objective optimization model that incorporates financial (NPV), technical (LOLP and curtailment), and policy-sensitive metrics.
- Quantify how policy incentives and schemes affect NPV, LCOE, and project bankability.
- Evaluate benchmark outcomes of policies in the U.S. and India based on various global references.
- Offer actionable insights to policymakers and project developers to improve investment attractiveness.

The primary novelty lies in the simultaneous optimization of NPV, LOLP, and curtailment while embedding dynamic, region-specific policy incentives directly into the optimization loop, providing a more holistic and realistic assessment of utility-scale HPP feasibility across different regulatory landscapes.

2. Methodology

This study develops a policy-integrated, multi-objective optimization framework for the optimal sizing of utility-scale HPPs comprising a wind power plant (WPP), a solar photovoltaic power plant (SPP), and a battery energy storage system (BESS). While individual component models for wind turbines, PV arrays, and BESS are well established in the literature, the novelty of our methodology lies in how these models are dynamically coupled with a techno-economic evaluation module and a region-specific policy layer within a unified optimization process.

Unlike previous HPP studies that focus on either technical or economic objectives in isolation, the proposed approach simultaneously addresses technical reliability (LOLP), operational efficiency (curtailment), and economic viability (NPV) while embedding dynamic regional policy incentives directly into the optimization loop. The methodological workflow consists of various stages: (i) acquisition and preprocessing of site-specific resource, load, cost, and policy data; (ii) applying established component performance modelling for wind, PV, and BESS to determine hourly generation, battery state of charge, and energy flows; (iii) techno-economic and policy integration; (iv) application of Multi-Objective Particle Swarm Optimization (MOPSO) to maximize NPV while minimizing LOLP and curtailment under operational and capacity constraints; and (v) policy scenario analysis for U.S. and Indian contexts, including sensitivity tests on policy parameters. This methodological integration, combining component-level technical models, site-specific economic evaluation, and policy scenario analysis within a single multi-objective optimization framework, enables a more realistic and actionable design process for utility-scale HPPs. While the individual models are well-known, their coordinated implementation with policy sensitivity represents a novel contribution, particularly for comparative studies between different policy environments.

2.1. Component Modelling

The performance of each subsystem within the HPP (Figure 1) is modeled using established engineering formulations widely recognized in the scientific community. These models are not themselves novel, but they form the necessary technical foundation for the integrated framework. These components are co-located and share the same grid interconnection, allowing optimized dispatch through a coordinated energy management strategy (EMS). The WPP and SPP subsystems provide the primary renewable energy inputs, while the BESS stores excess generation and supplies power during periods of low renewable availability. The battery also improves system reliability by reducing

curtailment and LOLP. The system's dispatch logic prioritizes renewable generation for meeting grid demand, charges the battery with surplus energy, and utilizes stored energy during generation shortfalls. Grid import is disabled, ensuring a fully self-sustained hybrid operation. The simplified block diagram of the system configuration is shown in Figure 1.

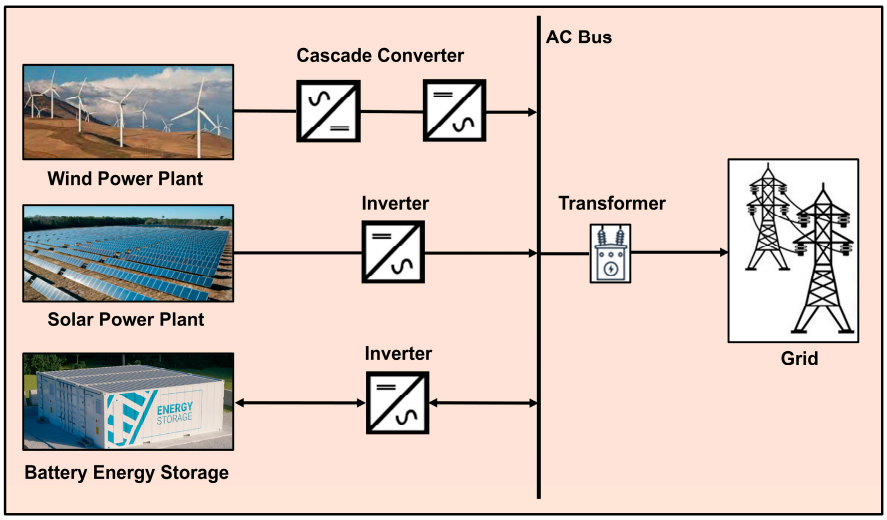


Figure 1. Schematic configuration of a proposed utility-scale HPP integrating wind, solar, and battery systems.

2.1.1. Wind Turbine Model

Many conventional wind turbine models approximate generation with a linear relationship between wind speed and power output. However, this simplification neglects the non-linear operating characteristics of real turbines, particularly the influence of cut-in, rated, and cut-out wind speeds. To address this, the present study employs the manufacturer's non-linear power curve, ensuring realistic modeling of turbine performance under variable wind conditions as demonstrated in Equation (1) [24].

$$P_{wt} = \begin{cases} P(t), & v_{cut-in} \leq v < v_r \\ P_r, & v_r \leq v \leq v_{cut-out} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where P_r, $P(t)$, v_{cut-in}, $v_{cut-out}$, and v are rated power, power output of wind turbine at time t, cut-in and cut-out velocity, and wind speed, respectively.

By using a non-linear cubic formulation, this model captures realistic performance transitions, in contrast to oversimplified linear models that can underestimate or overestimate turbine output. For intermediate analyses, a cubic approximation may be used to represent turbine behavior between cut-in and rated speeds [24].

$$P(t) = P_r \left(\frac{v^3}{v_r^3 - v_{cut-in}^3} \right) - P_r \left(\frac{v_{cut-in}^3}{v_r^3 - v_{cut-in}^3} \right) \quad (2)$$

In addition, this study also incorporated the height-dependent wind shear effect to account for increasing wind speeds at higher hub heights, as shown in Equation (3), significantly improving energy yield accuracy compared to ground-level measurements [9].

$$\frac{v_2}{v_1} = \left(\frac{h_2}{h_1} \right)^{\alpha} \quad (3)$$

v_1 and v_2 are wind speeds at heights h_1 and h_2. α is the wind shear exponent representing terrain dependence.

A common simplification is to use the 1/7th power law (α = 0.1429), but this may not reflect local atmospheric conditions and can lead to inaccurate wind speed estimates. In this study, hourly historical wind speed data were combined with a site-specific wind shear exponent, rather than the generic 1/7th value, to improve hub-height wind speed accuracy and, consequently, turbine generation estimates.

2.1.2. Solar Photovoltaic Model

This study uses hourly historical solar irradiance and ambient temperature data to better capture diurnal and seasonal variability. In addition, a shading factor is applied to correct the effective irradiance for partial shading losses. The PV output (P_{PV}) is calculated using Equation (4), which accounts for solar irradiance (G), ambient temperature (T), and panel specifications [9]. The model adjusts the standard power (P_{NPV}) by comparing the actual sunlight (G) to a standard level (G_{ref}) and considers temperature effects using the coefficient (kt), shading factor (S_f), and a reference temperature (T_{ref}).

$$P_{PV} = P_{NPV} \cdot \frac{G \cdot S_f}{G_{ref}} \cdot [1 + kt((T + (0.0256 \cdot G)) - T_{ref})] \quad (4)$$

By incorporating both temperature dependence and site-specific irradiance with shading adjustments, this formulation provides a more accurate estimate of PV generation than constant-efficiency or averaged-irradiance models.

2.1.3. Battery Energy Storage System Model

In much of the existing literature, battery storage is modeled with strong simplifications, often developed in the context of microgrids. These models typically assume constant charge/discharge rates and a fixed round-trip efficiency, overlooking variations in state of charge (SOC) and the cumulative effects of long-term cycling. While such assumptions simplify computation, they can lead to misleading estimates of usable storage capacity and system reliability when applied at utility scale. To avoid these limitations, this study represents the battery energy storage system (BESS) with practical SOC boundaries, dynamic charge and discharge constraints, and efficiency factors. This more detailed approach captures the operational realities of utility-scale storage, ensuring a realistic assessment of its role in (i) absorbing surplus renewable energy, (ii) supplying power during peak demand, and (iii) enhancing overall reliability of HPP operations [24,25].

The state of charge of the battery evolves according to charging, discharging, and depth-of-discharge limits, as expressed in Equations (5)–(7) [24,25].

Charging process

$$E_{charge}(t) = E_{charge}(t-1) \cdot (1-\sigma) + \left(E_{Total}(t) - \frac{E_{Load}(t)}{\eta_{inv}}\right) \cdot \eta_b \quad (5)$$

Discharging process

$$E_{discharge}(t) = E_{discharge}(t-1) \cdot (1-\sigma) - \left(\frac{E_{Load}(t)}{\eta_{inv}} - \frac{E_{Total}(t)}{\eta_b}\right) \quad (6)$$

Minimum capacity

$$E_{min} = (1 - DOD) \cdot S_b \quad (7)$$

Equations (5) and (6) track stored energy and discharge, respectively, over time, while Equation (7) ensures BESS longevity by preventing deep discharges. Here, $E_{charge}(t)$ and $E_{discharge}(t)$ represent BESS's stored energy and its released at time t. $E_{Total}(t)$ and $E_{Load}(t)$ indicate total renewable generation and demand at time t. $E_{charge}(t-1)$ and $E_{discharge}(t-1)$ represent the charging and discharging at the previous timestep $(t-1)$.

Key battery characteristics are self-discharge rate (σ), depth of discharge (DOD), and nominal capacity (S_b).

2.2. Techno-Economic Model

In the context of optimizing HPP under evolving policy landscapes, the following metrics: NPV, LOLP, and curtailment, offer a comprehensive assessment of both economic viability and system performance. Other economic metrics used to investigate are provided in the Supplementary Materials (Section S2).

2.2.1. Net Present Value (NPV)

NPV measures the overall profitability of the project by evaluating the discounted value of future cash flows. It provides a direct financial indicator to investors and policymakers regarding whether the project creates economic value. Since this study involves long-term policy scenarios and financial incentives, NPV helps quantify how these policies affect project bankability over the lifetime of the HPP. Therefore, this study applies NPV as shown in Equation (8) [26], which discounts annual revenues and costs, making it sensitive to both market and policy variations.

$$NPV = \sum_{t=0}^{T} \frac{R_t - C_{OM}}{(1+r)^t} - C_{cap} \quad (8)$$

where R_t is the revenue stream, C_{cap} is upfront capital expenditure adjusted for policy incentives, C_{OM} is annual operational expenses, and r is the discounted rate to future cash flows.

2.2.2. Loss of Load Probability (LOLP)

LOLP signifies the likelihood of an insufficient allocation of electrical energy to meet the demand, culminating in a Loss of Load Probability. It aids in the formulation of determinations regarding system architecture, capacity planning, and resource allocation to ensure a reliable provision of electricity to consumers. The LOLP value exists within the range of 0 and 1. A value of 1 indicates an unfulfilled load, whereas 0 denotes that the load is consistently satisfied. Mathematically, LOLP is represented in Equation (9) [9].

$$LOLP = \frac{\sum_1^T P_{unmet}(t)}{\sum_1^T P_{demand}(t)} \quad (9)$$

where P_{demand} and P_{unmet} represent the grid demand and load unmet, respectively.

2.2.3. Curtailment

Curtailment measures the proportion of surplus power (from WPP and SPP) not employed or stored (wasted power) due to constraints such as BESS capacity, grid limitations, or excessive generation in relation to demand and is mathematically delineated as demand. It is typically expressed as a percentage of the total power generated, highlighting the inefficiencies in energy utilization and the need for improved energy management strategies to minimize waste [9].

$$Curtailment = \frac{\sum_1^T P_{surplus}(t)}{\sum_1^T P_{WPP+SPP}(t)} \quad (10)$$

2.3. Problem Formulation

2.3.1. Objective Function

The formulation of objective functions in this study is designed to address the distinct priorities of key stakeholders in HPP deployment, such as investors (economic viability), grid operators (reliability), and policymakers (efficiency). Therefore, the present study

incorporates three objective functions (maximize NPV, minimize LOLP, and minimize curtailment) that were selected to comprehensively represent these multi-dimensional objectives capturing trade-offs between economics, reliability and curtailment (Equation (11)).

The optimization function (F) can mathematically be expressed as

$$F = [NPV, -LOLP, -curtailment] \tag{11}$$

By optimizing the parameters of NPV, LOLP, and curtailment collectively, the framework attains a financially sustainable configuration (investor confidence), a technically reliable HPP (grid operator satisfaction), and an efficient utilization of HPP assets (policy compliance). However, these objectives are inherently conflicting and cannot be optimized simultaneously in a straightforward way. Achieving higher reliability typically requires oversizing generation and storage, which increases capital expenditures and may reduce NPV due to higher upfront investment. Conversely, optimizing purely for economic returns often leads to leaner system sizing but at the cost of a higher probability of unmet demand (LOLP) during periods of low renewable output. Curtailment reduction improves the effective use of renewable resources and can increase revenues but usually demands additional investment in flexible storage or grid export infrastructure. This trade-off structure necessitates the formulation of a multi-objective fitness function, where the MOPSO algorithm balances exploration and exploitation to identify a Pareto-optimal set of solutions that represent acceptable compromises among profitability, reliability, and efficiency.

2.3.2. Constraints

The above optimization problem is subject to the following constraints, as illustrated in Equation (12).

$$\begin{gathered} P_{WPP} \geq 0 \\ P_{SPP} \geq 0 \\ P_{BESS} \geq 0 \\ E_{BESS} \geq 0 \\ 0.1 \leq SOC \leq 0.9 \\ LOLP \leq 0.1 \\ Curtailment \leq 0.1 \\ NPV > 0 \end{gathered} \tag{12}$$

where P_{WPP}, P_{SPP}, P_{BESS}, E_{BESS}, and SOC represent power generated from WPP, SPP, and BESS, respectively. Furthermore, E_{BESS} is the BESS energy, and SOC is the BESS state of charge.

2.4. Multi-Objective Particle Swarm Optimization

To address the complex trade-offs between economic, technical, and policy-driven objectives, this study employs a Multi-Objective Particle Swarm Optimization (MOPSO) framework. Building upon the foundational work of Kennedy and Eberhart [27] and further enhanced for multi-objective applications by Coello et al. [28], MOPSO effectively explores the high-dimensional solution space while maintaining a diverse Pareto front.

The algorithm uses Pareto dominance criteria and a crowding distance metric to maintain solution diversity. Particle updates are driven by personal and global best positions across the search space, where velocity (V_i) and position (X_i) updates are carried out as defined in Equations (13) and (14):

$$V_i(t+1) = \omega \cdot V_i(t) + C_1 \cdot R_1 \cdot (p_{besti}(t) - X_i(t)) + C_2 \cdot R_2 \cdot (g_{besti}(t) - X_i(t) \tag{13}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{14}$$

These equations balance cognitive (particle-specific) and social (swarm-wide) learning through carefully tuned parameters: inertia weight (ω) controls exploration–exploitation trade-offs, while acceleration coefficients (C_1, C_2) and random variables (R_1, R_2) guide particles toward individual (p_{best}) and global best (g_{best}) optima. The algorithms' biologically inspired flocking behavior makes it particularly effective for HPP optimization, as it efficiently navigates high-dimensional, non-convex solution spaces while approximating the complete Pareto frontier in a single run. The general flow diagram of the algorithm is illustrated in Figure 2.

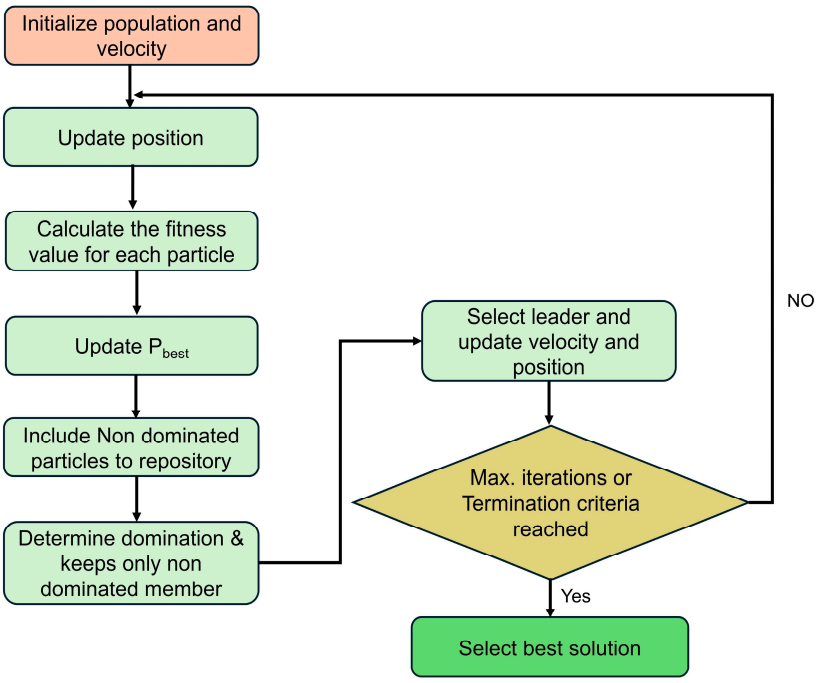


Figure 2. Workflow of the MOPSO algorithm (adapted from [9]).

2.5. Case Study Selection and Policy Context

To quantitatively assess the influence of regulatory and policy frameworks on the viability of HPPs, this research conducts a comparative analysis of two disparate policy environments, specifically selecting the United States and India as illustrative case studies owing to their divergent regulatory methodologies and varying stages of deployment maturity. The United States exemplifies a market-oriented, incentive-driven model devoid of mandates specific to hybrid technologies, while India embodies a policy-centric framework characterized by centralized planning and incentives specifically aimed at hybrids. In contrast, India has embraced a regulatory pathway specifically designed for hybrids through its National Wind–Solar Hybrid Policy (NWSHP), which overtly advocates for hybrid development as an integral aspect of its overarching energy security and decarbonization agenda [29]. The policy framework in India explicitly acknowledges HPPs as a strategic instrument for enhancing grid stability, facilitating decarbonization, and ensuring energy security, thereby rendering it a salient case for evaluating the impacts of targeted hybrid policies.

The contrasting regulatory frameworks of the United States and India provide a valuable foundation for examining how policy design affects the bankability, profitability, and scalability of utility-scale HPPs. This comparative policy mapping serves as a critical input to the scenario-based techno-economic analysis to be undertaken in subsequent sections. Table S2 highlight the major policy incentives and support in the U.S. and India that are applicable to HPP.

3. Data Collection and Assumptions

Weather data (wind speed, solar irradiance, and ambient temperature) were obtained from NASA POWER for a location in proximity to Lexington, Morrow County, Oregon (45.56° N, −119.634° W), as shown in Figure 3. The location was selected due to its extraordinary renewable resource potential and favorable policy framework. The location is characterized by robust complementary patterns of wind and solar energy, with wind velocities averaging 6.9 m/s at an elevation of 100 m (derived from 50 m NASA POWER data) and attaining maximum speeds of 21.92 m/s. Daily solar irradiance is recorded at an average of 247.62 W/m^2, with peak values reaching 1285.31 W/m^2 [30]. This study utilizes comprehensive 2023 NASA POWER meteorological data at 8760 hourly intervals. Under PPA terms, the suggested HPP setup is intended to produce 1730 GWh annually, with detailed resource characteristics visualized in Figure 4, including wind speed distribution, solar irradiance patterns, and grid demand profiles.

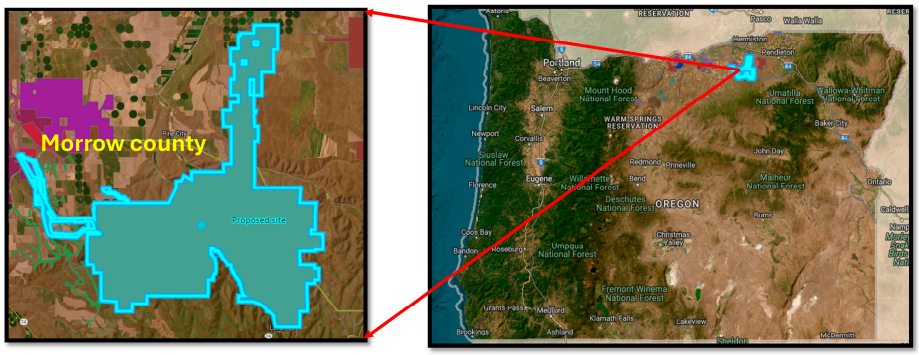


Figure 3. Geographic location of the study site in Lexington, Morrow County, Oregon, U.S. [31].

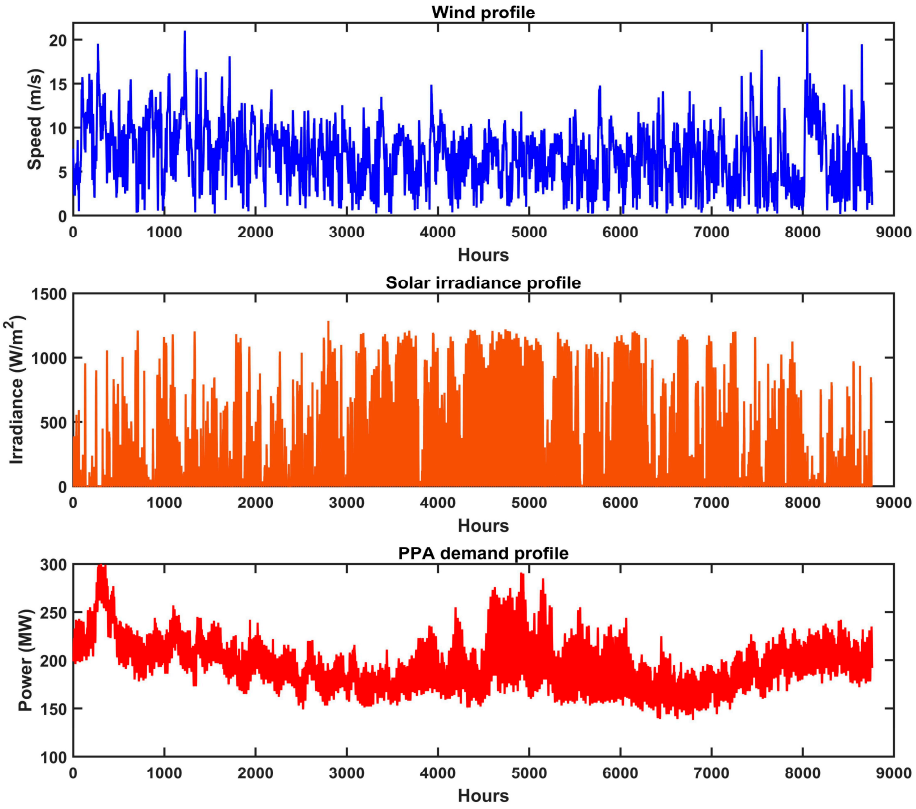


Figure 4. Annual hourly profiles of wind speed, solar irradiance, and PPA demand [32] used in system simulation and economic modeling.

To maintain analytical consistency and isolate the impact of differing policy environments, researchers used the same weather dataset for both the U.S. and India scenarios. This allows the analysis to isolate the impact of financial incentives and regulatory differences on system performance and economic outcomes. While this introduces a modeling simplification, it avoids confounding effects from spatial variability in solar and wind resources.

Economic parameters, including capital expenditures (CAPEXs) and operational expenditures (OPEXs) for HPP components, were obtained from the National Renewable Energy Laboratory (NREL) database [33–36]. Equipment, construction, electrical infrastructure, and labor are all included in capital expenditures, whereas maintenance, monitoring, and replacements are covered by annual O&M costs. In this study, grid interconnection and transmission costs were assumed to be zero to reflect conditions where co-located infrastructure is pre-established or subsidizes a common practice in renewable energy zones. Based on blended wind and solar PPA benchmarks [37], this research assumes a 30-year PPA at a fixed price of USD 63/MWh, with an average discount rate of 11% for India and 6% for the U.S. BESS is expected to achieve a 25-year operational lifespan by 2030. BESS degradation is modeled as a 0.5% annual linear reduction in usable capacity, reflecting typical lithium-ion battery performance for utility-scale storage applications. The detailed assumptions used in this study are provided in the Supplementary section. Tables S3–S5 in the Supplementary Materials provide the full list of technical and financial parameters and MOPSO parameters [9].

The results presented in this study are based on a case-specific configuration and set of assumptions chosen to isolate the effects of policy incentives on HPP viability. By employing identical meteorological data for both the U.S. and India, we isolate policy-driven effects from geographic variability in renewable resources. While this approach ensures a consistent comparative analysis, it inherently limits the direct extrapolation of absolute economic outcomes to regions with differing wind–solar complementarity profiles. Similarly, the assumed fixed PPA price, fixed discount rates, and exclusion of interconnection costs are scenario-specific parameters that may vary across markets. Technology cost and degradation rates are taken from NREL benchmarks and reflect 2023 conditions, meaning future cost declines could further improve project viability. These assumptions may change site-specific values, but the optimization framework and the observed trends, such as sensitivity of NPV to layered incentives and financing terms, remain applicable to other contexts when local inputs are used.

4. Results and Discussion

The optimal configuration of the HPP components is ascertained through the utilization of the MOPSO algorithm. The MOPSO algorithm was run in the MATLAB 2019b environment, using 100 particles and a limit of 50 iterations to find a good balance between speed and accuracy. The findings presented in this section are interpreted within the framework of the case-specific assumptions detailed in Section 3. While these methodological choices enable the isolation of policy effects on HPP viability, they necessarily constrain the direct numerical transferability of results to other contexts. Within these defined parameters, the optimization framework scrutinizes five critical dimensions: the results of optimization, analysis of energy management, an economic comparative assessment, and an evaluation of sensitivity.

4.1. System Sizing and Optimal Configurations

Significant trade-offs between NPV, LOLP, and curtailment across HPP configurations are depicted in Table 2 and the Pareto front (Figure 5). Solutions characterized by high NPV (USD 165 million) illustrate that substantial financial returns can be achieved alongside

moderate reliability (LOLP < 8.5%) and low curtailment (<4%). Nonetheless, the pursuit of extreme reliability incurs considerable costs: Configurations exhibiting ultra-low LOLP (2.5%) experience elevated curtailment (18.24%) and a markedly diminished NPV (USD 83.56 million), thereby exemplifying the economic repercussions associated with over-engineering for near-optimal reliability. Conversely, systems optimized for low curtailment often sacrifice either profitability or reliability. These complex interdependencies emphasize the need for multi-objective optimization, where the optimal HPP design balances all three factors rather than focusing on a single metric. With 283 MW of WPP, 20 MW of SPP, and 500 MWh of BESS, the proposed balanced-optimization HPP shows financial soundness with an NPV of USD 165.46 million and LCOE of USD 0.065 kWh. Operational performance continues to be proficient, with LOLP reported at 6.78% and curtailment kept at 5%.

Table 2. Selected optimal result from MOPSO for HPP.

Parameters	Max NPV	Min LOLP	Min Curtailment
WPP (MW)	283	286	248
SPP (MW)	20	60	21
BESS (MWh)	500	888	557
NPV (USD M)	165.46	60.98	5.01
LOLP (%)	6.78	4.2	14.78
Curtailment (%)	5	4.59	0.42

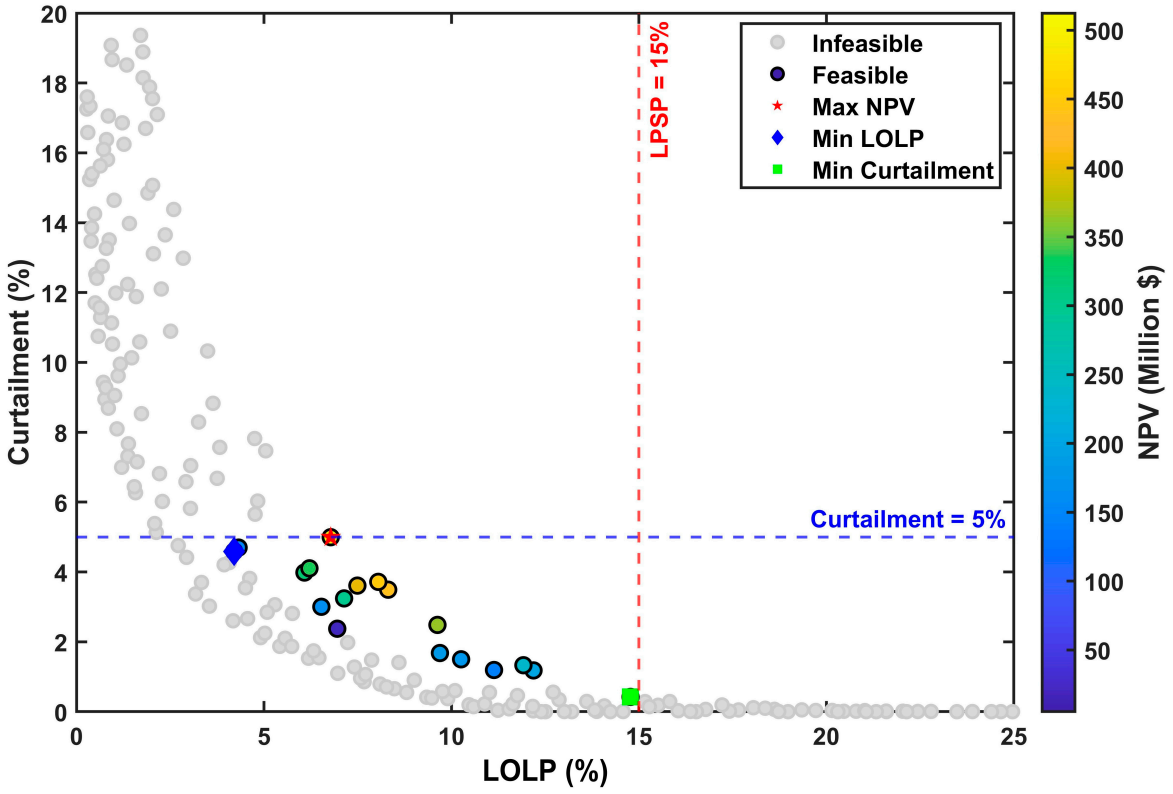


Figure 5. Pareto plot showing the tradeoff between NPV, LOLP, and curtailment using MOPSO.

All subsequent analyses, including operational behavior, economic performance, and sensitivity examinations, adopt the NPV-optimized configuration as their baseline.

Algorithm Convergence and Pareto Front Robustness

This study employs an MOPSO framework to jointly optimize NPV, LOLP, and curtailment. While explicit convergence metrics, such as hypervolume, generational distance,

or spread, were not tracked, this simplification was intentional to reduce computational overhead and focus on identifying optimal configurations under varying policy scenarios rather than algorithm benchmarking.

Despite the absence of formal convergence diagnostics, the resulting Pareto fronts exhibit strong diversity, clearly capturing the trade-offs among competing objectives. To assess solution robustness, a Pareto plot (LOLP vs. curtailment, colored by NPV) is provided in Figure 5. The well-distributed non-dominated solutions suggest that the swarm effectively explored the search space without premature convergence. Future research could incorporate formal convergence analysis (e.g., hypervolume indicators or spacing metrics) to further validate algorithmic performance and enhance reproducibility.

4.2. Energy Management System Performance and Energy Balance

Figure 6 illustrates the 24 h energy dispatch and battery SOC trends for the HPP. The system demonstrates effective use of wind generation for overnight charging and midday solar support, with battery discharging during periods of insufficient renewable generation. SOC fluctuates in response to load and generation dynamics, rising during periods of excess wind and solar (e.g., 3–6, 12–16, and 17–24), remaining flat when fully charged (6–9), and declining during energy deficits (2, 10–12, and 17), when unmet load also appears. This cyclical behavior highlights the role of battery storage in managing renewable intermittency and curtailment.

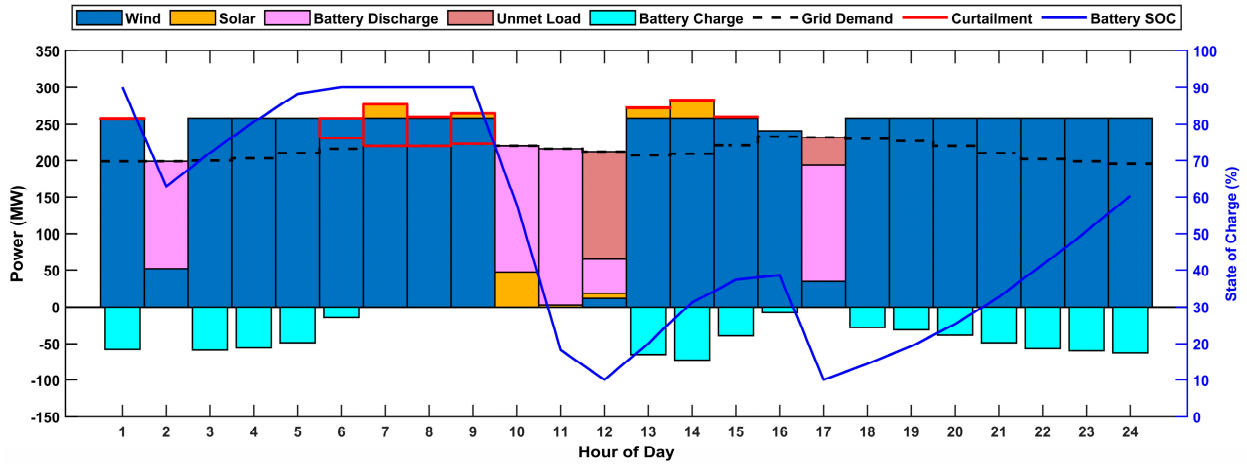


Figure 6. Hourly energy dispatch and battery SOC profile over a 24 h period (adapted from [9]).

Table 3 complements this profile by summarizing annual energy flow, storage use, curtailment, and unmet demand. These results underscore the critical balance between renewable availability, storage capacity, and demand obligations in ensuring operational stability.

Table 3. Annual energy dispatch in GW/GWh.

PPA Demand	WPP	SPP	BESS Discharge	BESS Charge	Curtailed	Unmet Load
1730.2	1705.9	38.65	271.35	313.68	81.59	121.94

4.3. Policy-Driven Economic Assessment

This study evaluates the economic feasibility of utility-scale HPPs under divergent policy regimes, using an optimized system configuration derived from MOPSO results (Table 2). The analysis compares baseline (policy-neutral) and policy-supported scenarios through NPV and LCOE (Table 4).

Table 4. Economic metrics using policy support for the U.S. and India.

Metrics	Baseline	Policy Support (Change %)	Baseline	Policy Support (Change %)
	U.S.		India	
NPV (USD M)	−355.74	344.93 (+197)	−867.75	64.06 (+107.4)
LCOE (USD/kWh)	0.067	0.059 (−11.94)	0.099	0.04 (−59.6)

In the baseline scenario without policy support, both regions showed negative NPVs and failed to achieve a discounted payback, highlighting poor economic viability under purely market-driven conditions. The U.S. performed comparatively better due to a higher PPA rate and lower interest rate. With the inclusion of policy incentives ITC/PTC in the U.S. and AD/GBI/VGF in India, project economics improved substantially. In the U.S., NPV increased from −USD 355 M to +USD 345 M, and LCOE dropped by ~12%. In India, policy support shifted NPV from −USD 868 M to +USD 64 M and cut LCOE by nearly 60%. These findings emphasize that policy mechanisms are critical for making HPPs bankable, especially in emerging markets. While both countries benefit from incentives, the layered U.S. policies yield stronger financial performance, suggesting that India's hybrid sector could benefit from deeper fiscal support and regulatory clarity.

4.4. Sensitivity Analysis

4.4.1. Policy Uncertainty

As capital-intensive ventures, HPPs depend significantly on government backing, which may fluctuate due to budgetary constraints, political shifts, or policy changes. This study examined this risk through scenario testing of three support levels: full, reduced, and eliminated (Table 5). Results (Table 6) underscore policy consistency as a critical factor, especially in developing economies.

Table 5. Scenario-based simulation.

Scenario	Description	
	U.S.	India
Case 1	100% PTC support	100% GBI support
Case 2	50% PTC reduction	50% GBI reduction
Case 3	100% elimination	100% elimination

Table 6. Comparative economic performance under policy uncertainty scenarios in U.S. and Indian markets.

Metrics	Case 1	Case 2	Case 3	Change % (Case 1)	
				With Case 2	With Case 3
U.S.: NPV (USD M)	369.85	185.85	123.11	−49%	−66.71%
India: NPV (USD M)	29.81	−26.67	−44.66	−189.48%	−249.78%

In the U.S., phasing out the PTC after year 10 reduced NPV by ~67%. Indian projects proved more vulnerable: Removing GBI led to a 250% drop in NPV and failed to break even over 30 years. These outcomes confirm that while U.S. projects benefit from resilient market dynamics, Indian HPPs remain critically dependent on robust, layered policy support.

4.4.2. NPV-Based Breakeven Analysis with Policy Support

A breakeven contour analysis (Figures 7 and 8) further explores incentive interactions. In the U.S., either a high ITC (≥45%) or a strong PTC (~USD 16/MWh) ensures profitability,

though combining both yields optimal financial outcomes. In contrast, Indian projects require paired incentives: Only when GBI exceeds USD 0.16/kWh or AD surpasses 40% do projects break even. This underlines the need for integrated support frameworks in high-risk markets.

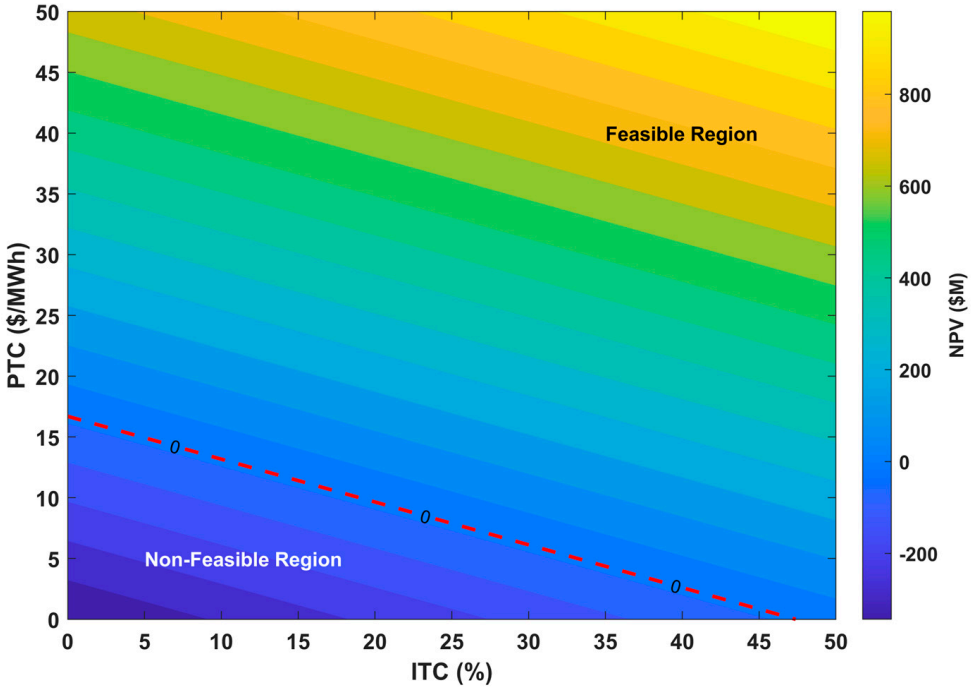


Figure 7. Contour plot showing combinations of ITC and PTC required to ensure financial feasibility of HPPs in the U.S.

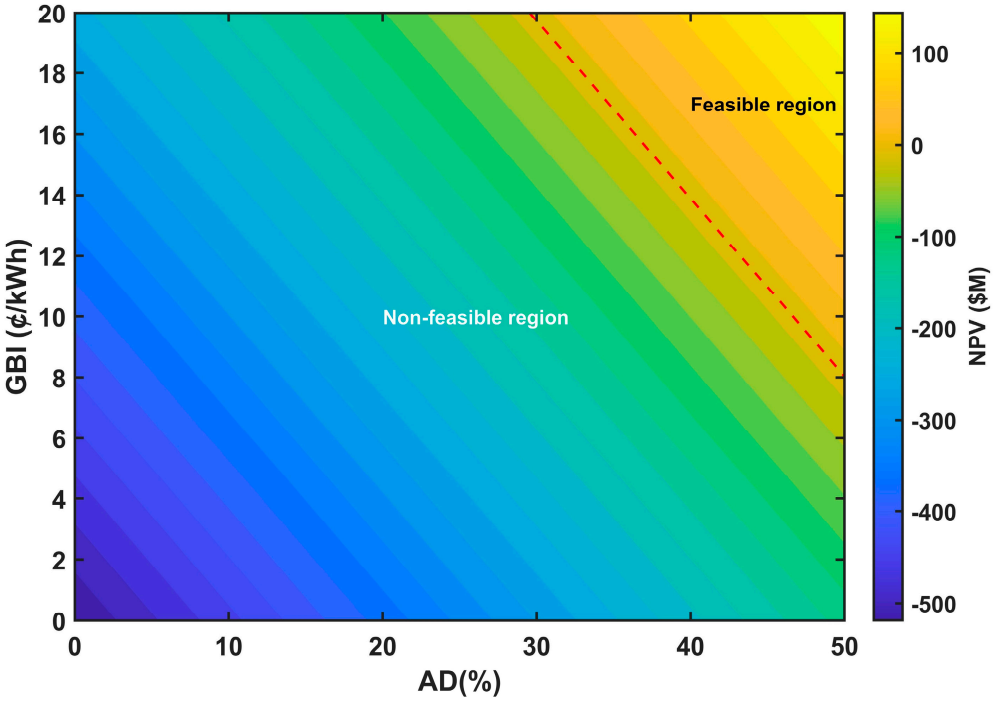


Figure 8. Contour plot for India showing breakeven combinations of AD and GBI.

4.4.3. Risk Assessment

Tornado plots (Figures 9 and 10) evaluate how strong HPP investments are in the U.S. and India by measuring how changes in important policy and financial factors impact

NPV. This analysis identifies the most critical factors influencing project feasibility under uncertainty. The financial feasibility of HPPs is highly sensitive to two key macroeconomic variables: the PPA price (driving revenue) and the interest rate (affecting financing costs).

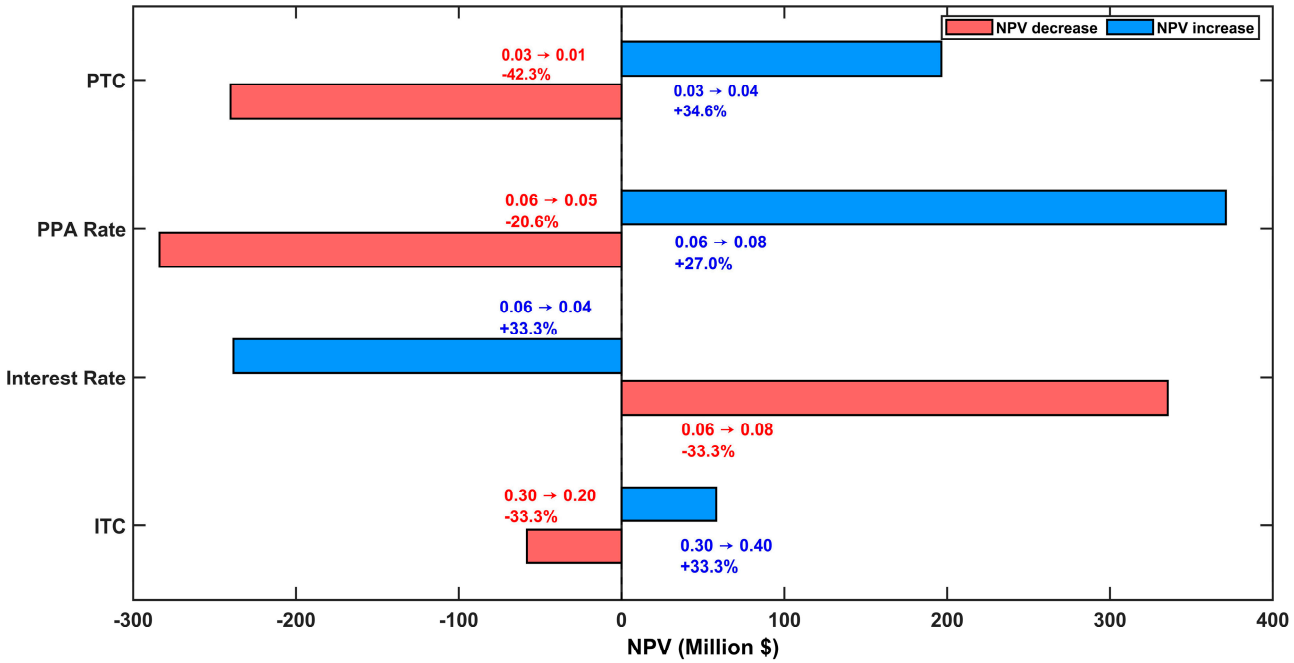


Figure 9. NPV response to policy and market parameter fluctuations in the U.S.

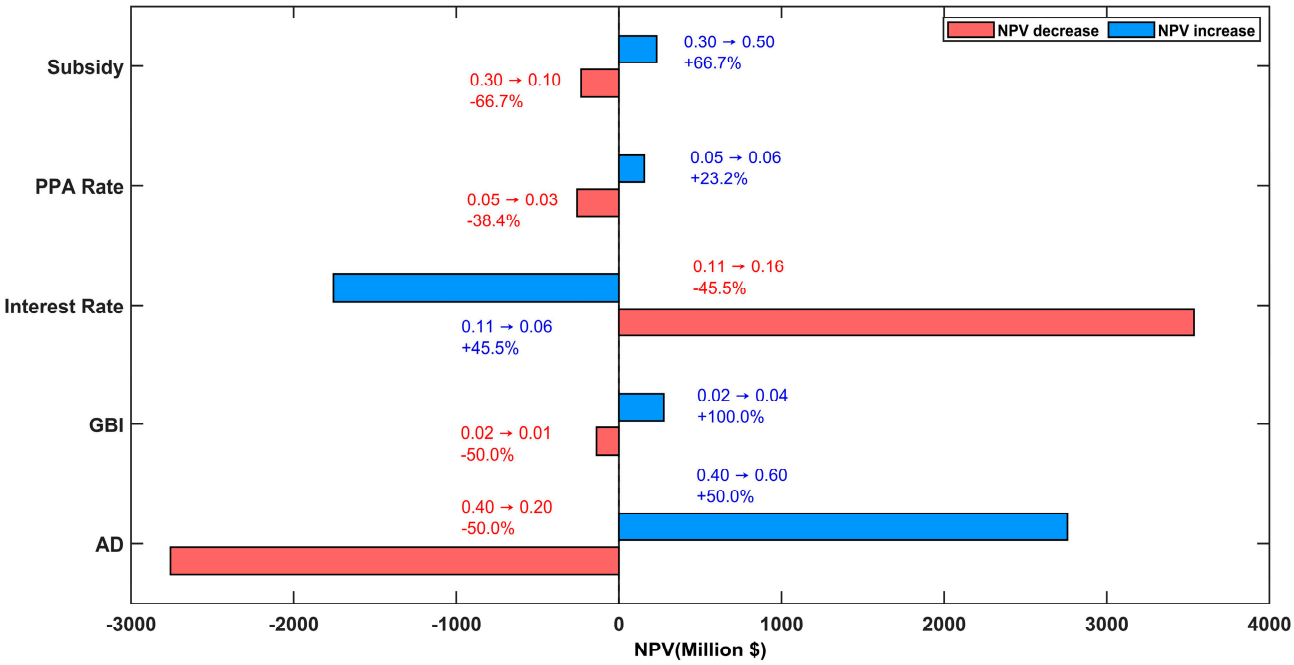


Figure 10. NPV response to policy and market parameter fluctuations in India.

In the U.S., a 2% increase in the baseline interest rate (6%) reduced NPV by over USD 325 million, while raising the PPA rate to USD 0.08/kWh increased NPV by ~USD 375 million, underscoring the outsized influence of financing costs and revenue conditions. In contrast, tax incentives (ITC and PTC) had a secondary but still meaningful impact, improving NPV by up to ~USD 58 million when maximized. This suggests that while

such policies enhance viability, they serve a supplementary role relative to market-driven financial variables.

For India, sensitivity to policy and financing parameters was markedly more pronounced. A reduction in AD from 40% to 20% decreased NPV by ~USD 2.8 billion, while an increase to 60% raised NPV by ~USD 1.4 billion, highlighting the criticality of capital recovery mechanisms. Similarly, an interest rate hike from 9.5% to 16% eroded NPV by over USD 3.2 billion, reflecting India's acute exposure to financing risks. Performance-based incentives, GBI, and capital subsidies also exerted significant influence, though less than AD and interest rates. Notably, the tornado plot exhibited asymmetric downside risks, with NPV disproportionately sensitive to adverse changes in AD or financing costs.

Overall, the analysis highlights that for India, renewable energy economics are more dependent on aggressive policy support, whereas in the U.S., market-based financial terms like interest rates and PPA contracts play a more decisive role in shaping investment feasibility.

4.4.4. Combined Policy Incentive and Financial Sensitivity Analysis

The financial viability of HPPs is highly sensitive to two macroeconomic factors: the PPA price, which determines project revenue, and the interest rate, which directly affects financing costs and capital recovery. To assess this interaction, this study performs a two-variable sensitivity analysis across a range of interest rates (3.5–15%) and PPA rates (USD 0.03–USD 0.1/kWh), under policy support conditions for both India and the U.S.

The results, presented in Figures 11 and 12, highlight the substantial impact of combined policy incentives on the economic viability of HPPs in the U.S. and India. In the U.S., the interaction between the ITC and PTC significantly broadens the feasible region, allowing for project breakeven at lower PPA rates (approximately USD 0.035–USD 0.06/kWh) across a wide range of interest rates. The red contour line, denoting the NPV = 0 threshold, shifts downward under combined support, indicating stronger financial resilience and higher profitability even in scenarios with rising financing costs. In India, the combined effect of AD, GBI, and capital subsidy similarly expands the breakeven region. The analysis indicates that viability can be achieved at lower PPA rates (as low as USD 0.035/kWh) and higher interest rates (up to 15%), reflecting improved economic performance despite India's high cost of capital. The results demonstrate the need for layered policy frameworks in both countries, where coordinated capital and performance-based incentives are essential to unlock investment and ensure the long-term financial sustainability of HPPs.

4.5. Energy Management Scope and Limitations

The EMS in this study prioritizes renewable dispatch and storage utilization under a fixed-price PPA framework, with grid import disabled to ensure analytical consistency across the two regulatory contexts (U.S. and India). While this approach captures core dispatch behavior and facilitates techno-economic comparisons under policy variations, it excludes dynamic pricing, reserve market participation, and ancillary service revenue factors that could enhance project economics.

Incorporating these mechanisms could enable revenue stacking, battery arbitrage during price fluctuations, and monetization of grid services (e.g., frequency regulation and spinning reserve), potentially reducing LOLP and improving NPV. However, modeling such strategies requires granular pricing data, dynamic market access rules, and co-optimization algorithms, which are unavailable publicly at this moment.

To maintain neutrality and comparability, these elements were deliberately omitted. This simplification aligns with this study's primary objective: evaluating the impact of national-level policy incentives on hybrid power plant viability. Future research will extend

the EMS framework to integrate market-based dispatch and ancillary service participation, enabling a more comprehensive revenue potential assessment.

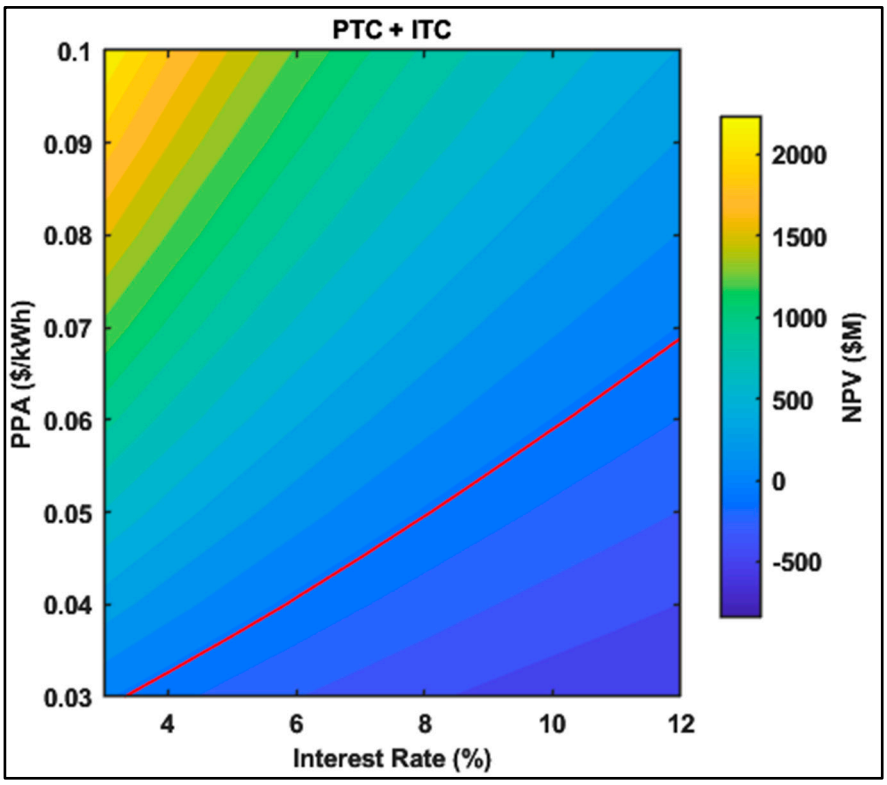


Figure 11. Impact of financial incentives on the economic feasibility of HPP across varying interest rates and PPA levels in the U.S. The red contour indicates the breakeven boundary (NPV = USD 0 M).

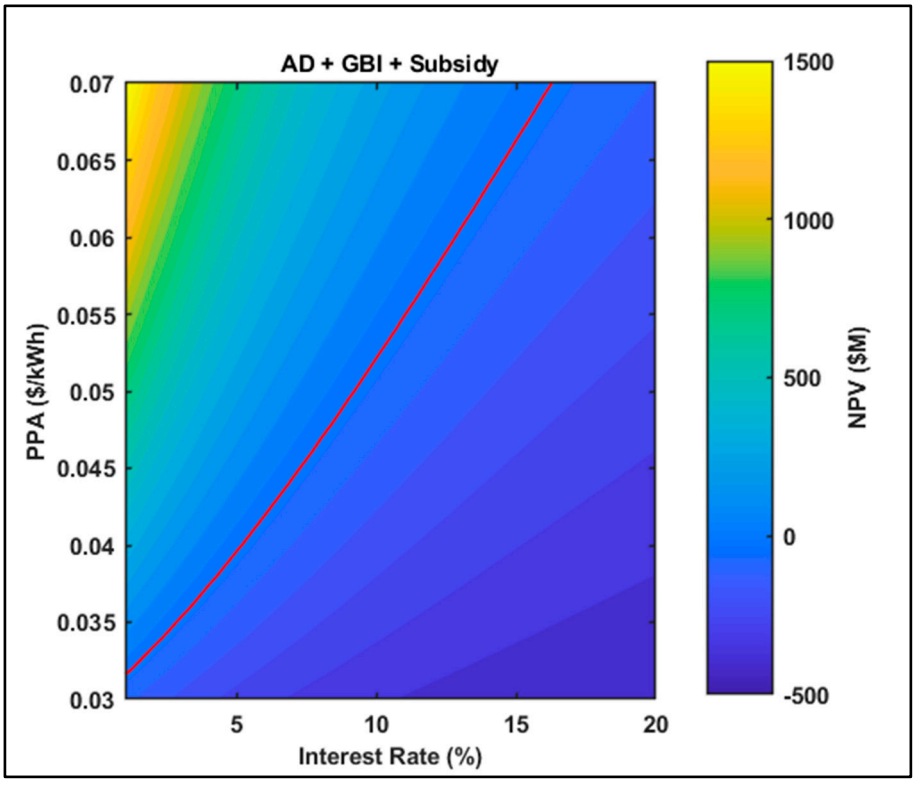


Figure 12. Impact of financial incentives on the economic feasibility of HPP across varying interest rates and PPA levels in India. The red contour indicates the breakeven boundary (NPV = USD 0 M).

4.6. Technology-Wise LCOE Breakdown

To better understand the cost structure of the HPP, a component-wise LCOE analysis was conducted for both the U.S. and India. This breakdown distributes the total system LCOE according to the proportion of energy delivered by wind, solar, and battery storage, as well as their respective annualized costs. The total LCOE was not computed as a simple arithmetic average but rather as a weighted average based on the energy share of each technology in meeting the annual PPA demand (1730.2 GWh). The results, presented in Table 7, show that WPP is the most cost-effective component in both countries, with individual LCOEs of USD 0.0237/kWh (U.S.) and USD 0.0171/kWh (India), contributing approximately 85% of the delivered energy. BESS, despite supplying only 13–14% of the energy, contributes disproportionately to the total LCOE USD 0.2430/kWh in the U.S. and USD 0.1757/kWh in India, due to higher capital and operational costs. SPP, while present at a small scale (~2% of energy share), had a moderate LCOE in both cases. These findings highlight the dominance of BESS in system cost and point out that it requires targeted incentives, particularly in storage deployment, to reduce the overall LCOE and improve economic viability.

Table 7. LCOE breakdown for each component.

Technology	Share (%)	LCOE Contribution (%)	LCOE (USD/kWh)	
			U.S.	India
WPP	84.61	37.1	USD 0.0237	USD 0.0171
SPP	1.92	2.3	USD 0.0647	USD 0.0467
BESS	13.46	60.6	USD 0.2430	USD 0.1757
Total	100.0	100.0	USD 0.0540	USD 0.0390

Note: Individual LCOEs are calculated by dividing each technology's annualized cost by its share of energy delivered to the load. The total LCOE is a weighted sum, not the arithmetic average of individual values.

4.7. Comparison with Previous Studies

While direct comparisons of HPP optimization studies are challenging due to variations in system configurations, load profiles, weather conditions, and economic assumptions, as well as limited public data and proprietary constraints, this study's techno-economic results have been benchmarked against reported values from reputable sources. Table 8 presents a comparison with global cost-performance metrics to evaluate the realism and competitiveness of the proposed HPP design.

Table 8. Comparison of proposed HPP LCOE with benchmark studies [33,38,39].

References	LCOE			
	Wind (USD/kWh)	Solar (USD/kWh)	BESS (USD/kWh)	HPP (USD/kWh)
NREL	0.029	0.043	0.098	0.037
IRENA	0.038	0.049	0.093 *	0.042
Bloomberg	0.037	0.035	0.093	0.039
Present study (U.S.)				0.054
Present study (India)	-	-	-	0.039

* Consider from Bloomberg, as no value was provided.

The analysis confirms that while the Indian system achieves a competitive LCOE (≈USD 0.039/kWh), the U.S. system (≈USD 0.054/kWh) remains marginally above benchmark ranges due to differences in the incentives layer. This comparison supports the model's effectiveness and highlights the importance of policy and financial structuring.

4.8. Limitations and Future Work

While the proposed framework offers a robust policy-integrated techno-economic evaluation of HPPs, several simplifications were necessary for scope clarity and consistency:

- Transmission and interconnection costs were not incorporated due to data limitations. For project-level feasibility, future work will include site-specific interconnection and transmission charges.
- While the MOPSO algorithm showed strong solution diversity, convergence metrics were not tracked. These will be included in future evaluations.
- This study focuses on techno-economic performance under structured policy incentives and does not explicitly model environmental, land-use, or permitting constraints, which can significantly affect project timelines, costs, and siting feasibility. Their exclusion was intentional to maintain focus on incentive-driven modeling. Future work should integrate these spatial and regulatory factors to support holistic planning and risk mitigation in HPP development.
- Oregon's weather dataset was applied to both regions to isolate policy effects. Region-specific weather data will be incorporated in follow-up work.
- The analysis does not include grid interconnection and transmission cost and market-based revenue streams such as carbon credits, capacity payments, and ancillary services. These mechanisms could substantially improve project economics, particularly by enhancing the value proposition of battery storage, which accounts for a major share of system costs. For example, carbon credit schemes or renewable energy certificates could reward clean generation, while capacity payments and grid services (e.g., frequency regulation) could offer additional income streams. Although detailed modeling of these revenues was beyond the scope of this work, their inclusion in future studies could provide a more comprehensive view of long-term viability and investor attractiveness.
- This study does not model dynamic inverter sizing, AC/DC coupling, or adaptive EMS. Future research could examine how these affect flexibility and performance.
- Carbon credits, ancillary services, and capacity payments were excluded but may substantially enhance NPV and revenue stability. Future work will model these mechanisms to reflect the full revenue potential.
- The MATLAB simulation and optimization framework is currently under active research and collaboration and is not publicly released. A future open-source version may follow upon project completion.

Addressing these areas will allow for a more complete and granular assessment of hybrid project feasibility under real-world deployment conditions.

5. Conclusions and Recommendations

This study assesses the economic viability of utility-scale HPPs under differing policy regimes in the U.S. and India. Using a financial model incorporating real-world incentives (ITC, PTC, AD, GBI, capital subsidies), this study evaluates impacts on NPV and LCOE.

The results clearly demonstrate that without incentives, HPPs are financially unviable in both markets (U.S.: −USD 355 M; India: −USD 868 M). Structured policy support dramatically improves outcomes (U.S.: USD 470 M; India: USD 64 M) and LCOE of USD 0.055/kWh (U.S.: −18%) and USD 0.04/kWh (India: −60%).

Sensitivity analysis reveals PPA rates and interest rates as critical drivers. A 2% interest rate hike reduced India's NPV by USD 3.2 B (U.S.: USD 325 M).

Integrated, HPP-specific incentives are essential for bankability, particularly for battery storage. Long-term policy stability, PPAs, and grid-service monetization are key to scaling HPP deployment.

While the numerical results presented here are based on the specific resource, cost, and policy profiles of the U.S. and India, the methodology is adaptable to other geographical contexts. Replication requires the substitution of local datasets for renewable resource availability, demand patterns, cost structures, and applicable policy incentives. The modular nature of the optimization framework ensures that it can be expanded to incorporate other generation and storage technologies (e.g., concentrated solar power, pumped hydro, and hydrogen storage) or additional operational constraints (e.g., grid stability limits and market bidding strategies).

Future work should focus on applying the proposed methodology to a wider set of climatic, policy, and market conditions to produce comparative insights across contexts. This includes refining the model's predictive accuracy and integrating stochastic approaches for uncertainty quantification. Beyond the core techno-economic findings, this study acknowledges key modeling simplifications, including the exclusion of carbon credits, ancillary revenues, siting constraints, and dynamic system designs. Section 4.8 summarizes these. By providing a replicable, policy-aware optimization framework, this study offers a pathway for global deployment of reliable, cost-effective, and policy-aligned utility-scale HPPs.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en18174608/s1. Supplementary materials include Tables S1–S5, which present global HPP policy frameworks, U.S. and India tax incentives, techno-economic parameters for wind, solar, and battery systems, policy-supported assumptions, and MOPSO algorithm parameters respectively. Section S2 defines the LCOE, and Section S3 outlines key modeling assumptions related to weather data, taxation, policy support, revenue sources, and grid constraints. References [40–48] are cited in Supplementary Materials.

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Nomenclature

AD	Accelerated Depreciation
ASC	Annualized System Cost
BESS	Battery Energy Storage System
CAISO	California Independent System Operator
CAPEX	Capital Expenditure
EEG	Erneuerbare Energien Gesetz (German Renewable Energy Act)
FERC	Federal Energy Regulatory Commission
FiP	Feed in Premium
FiT	Feed in Tariffs
GBI	Generation-Based Incentives
HPP	Hybrid Power Plant
IRR	internal Rate of Return
ITC	Investment Tax Credits
LCOE	Levelized Cost of Energy
LOLP	Loss of Load Probability

MOPSO	Multi-Objective Particle Swarm Optimization
NAC	Network-Access Contracts
NPV	Net Present Value
NWSHP	National Wind–Solar Hybrid Policy
OPEX	Operational Expenditure
PCC	Point of Common Coupling
PPA	Power Purchase Agreements
PTC	Production Tax Credits
RES	Renewable Energy Sources
RPS	Renewable Portfolio Standard
SPP	Solar Power Plant
VGF	Viability Gap Funding
WPP	Wind Power Plant

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