

## Article

# Hybrid Metaheuristic-Based Probabilistic Planning of Weak Power Grids with Renewable Generation and Hydrogen Energy Storage

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## Abstract

The large-scale integration of wind turbine generators (WTGs) and photovoltaic (PV) generation increases operational uncertainty and can exacerbate stability limitations in weak transmission networks, motivating the use of green hydrogen energy storage systems (HESS). This paper presents a probabilistic planning framework for the joint siting and sizing of HESS to support hybrid WTG–PV integration under stochastic wind, solar irradiance, and load conditions. The proposed framework explicitly couples Monte Carlo-based probabilistic power flow with weak-grid security constraints by enforcing FVSI-based voltage-stability limits and an SSI-based system-strength requirement within the optimization loop, rather than treating these indices as post-analysis checks. The planning problem is formulated using a weighted-sum scalarization to minimize life-cycle carbon footprint and active power losses, subject to security constraints based on the Fast Voltage Stability Index (FVSI) and a system-strength constraint expressed through a System Strength Index (SSI). To solve the resulting constrained, nonlinear optimization problem, a sequential hybrid metaheuristic that couples Whale Optimization (exploration) with Osprey Optimization (exploitation) is developed. The framework is implemented in MATLAB using MATPOWER and evaluated on a modified IEEE 39-bus system. Simulation results report an annual carbon footprint of 22.16 Mt CO<sub>2</sub>eq/yr, an improvement of 9.2% and 5.3% relative to PSO and GA/PSO baselines, respectively, while increasing the weakest-bus SSI to 4.68 (bus 7). The resulting HESS design comprises a 296.9 MW electrolyzer, a 262.7 MW fuel cell, and 28,012 kg of hydrogen storage.

**Keywords:** carbon footprint (CFP); Fast Voltage Stability Index (FVSI); hydrogen energy storage system (HESS); inverter-based energy resources (IBRs); Probabilistic Power Flow (PPF); System Strength Index (SSI)



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## 1. Introduction

The growing global demand for energy has positioned renewable energy sources (RES) as key contributors to future power systems. However, the variable and unpredictable nature of RES presents significant challenges for integration, particularly in maintaining

grid stability, ensuring reliable supply, and achieving consistent power dispatch from clean sources [1–4]. To address these challenges, robust energy storage solutions are essential. These systems enable the capture of excess generation during peak periods and facilitate energy availability during times of low production.

While battery energy storage systems (BESS) are widely adopted for short-term applications, they are constrained by limitations such as self-discharge rates and relatively low energy density. In contrast, hydrogen energy storage systems (HESS) offer a compelling alternative for long-duration storage, with advantages including higher energy density and environmentally benign operation [5]. Unlike lithium-ion batteries, HESS exhibit minimal degradation over time and maintain efficiency across extended lifespans [6]. Furthermore, green HESS technologies offer a sustainable pathway for energy storage. These systems utilize surplus electricity from renewable sources to produce hydrogen via water electrolysis. When reconverted to electricity through fuel cells, the only byproducts are water and heat, making the process both clean and ecologically harmless [7].

A considerable body of research has explored the integration of renewable energy sources (RES) with energy storage systems (ESS), adopting diverse methodologies ranging from optimization techniques to planning frameworks. Several studies have focused on meta-heuristic algorithms for system optimization. For instance, an enhanced harmony search algorithm was developed in [8] to minimize operational costs and improve reliability in microgrid design, incorporating different ESS technologies to enhance convergence speed and solution quality. Similarly, ref. [9] introduced the Moth-Flame Optimization algorithm (MFO) to optimize hydro and thermal power scheduling that integrates solar, wind, and electric vehicles (EVs), highlighting the potential of EVs to mitigate renewable variability. Further, ref. [10] compared the performance of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in designing a hybrid PV/wind/biomass system with the purpose of optimizing the cost of energy (COE). In [11], the authors applied K-means clustering combined with GA to determine the optimal sizing of a battery energy storage system (BESS) for grid-scale renewable power smoothing. Additionally, a Red Panda Optimization approach was used in [12] for the planning of off-grid renewable-hydrogen systems with EV charging, yielding notable reductions in cost and environmental impact.

Another stream of work emphasizes multi-objective planning frameworks that integrate generation, transmission, and storage. In [13], a multi-tier planning scheme was developed to align coordinated investment strategies among transmission system operators (TSOs) and private investors in hybrid wind-storage plants, involving transmission expansion, location, and capacity decisions. Transmission line congestion and its influence on RES/ESS allocation were further examined in [14], where a multi-objective optimization framework prioritized robustness while considering market investment signals. Ref. [15] extended this perspective by jointly planning generation, transmission, ESS, and demand response (DR), ensuring flexibility and environmental sustainability. A related approach was demonstrated in [16], where distributed generation (DG) was co-optimized with distribution automation (DA) devices through nonlinear and linear models to minimize overall system cost and improve technical reliability.

Hybrid renewable and storage integration has also been widely studied at both microgrid and city levels. The work in [17] optimized wind, PV, BESS, and hydrogen storage capacities for a case study in Cameroon, identifying cost-effective configurations to meet load demand. In [18], an integrated energy hub system was proposed to coordinate electrical, thermal, cooling, and water subsystems, optimizing costs and groundwater dependency through multi-objective methods. Similarly, ref. [19] presented a price-based DR framework for smart homes within an energy hub that included thermal and electric energy storage, demonstrating short-term operational planning benefits in cost and emission

reduction. A comparable model was later extended in [20], confirming the effectiveness of energy hubs with stochastic optimization for handling uncertainties in demand and renewable generation.

In the context of unit commitment and system operation, ref. [21] formulated a mixed-integer linear programming (MILP) model in MATLAB to coordinate RES, BESS, and conventional generation under nonlinear constraints. At a larger scale, ref. [22] established a stochastic energy management framework for virtual power plants (VPPs), integrating RES, EVs, and DR while considering uncertainties in load and market prices through the Unscented Transform. A similar approach was adopted in [23], where a stochastic optimal power flow framework was proposed for renewable-based VPPs, optimizing active/reactive power while balancing cost, losses, and voltage stability. Ref. [24] further investigated optimal VPP placement and sizing under extreme events such as earthquakes and floods, formulating a bi-objective stochastic problem solved with a hybrid meta-heuristic algorithm.

Recent studies have also explored comparative planning techniques and stability-oriented frameworks. In [25], an OPF-based model was proposed for the combined operation of thermal units and RES in a modified IEEE 30-bus system. While effective in minimizing network losses and operational costs, its single-objective formulation and reliance on fixed RES placement limited optimization flexibility compared to multi-objective, location-aware methods. Ref. [26] adopted a network partitioning strategy to allocate and size RES/ESS across sub-networks, improving local self-sufficiency but prioritizing capacity maximization over global carbon footprint and efficiency objectives. Meanwhile, ref. [27] focused on weak-grid reliability by optimizing BESS allocation in the IEEE 39-bus system using Adaptive Grey Wolf Optimization (AGWO). Their approach integrated short-circuit ratio (SCR) screening and reliability indices such as EENS, SAIFI, and SAIDI, alongside voltage and frequency stability metrics. Although this work demonstrated significant reliability gains, it did not explicitly address carbon footprint or system-strength considerations, which are central to more recent RES/HESS integration frameworks. Finally, intelligent and data-driven approaches have been applied to energy management. In [28], an intelligent energy management system with risk-averse flexibility (RFEMS) was developed for micro-grids, employing hybrid deep learning models for forecasting renewable generation, load, and prices. The optimization problem was solved using linearized stochastic programming with robust features, yielding improved forecasting accuracy and system operation. In a similar vein, ref. [29] proposed a three-level objective optimization framework for dynamic pricing strategy and network reconfiguration, considering reliability, operational costs, and stochastic uncertainties, solved through a hybrid meta-heuristic approach.

Despite the extensive body of literature on RES–HESS planning, several critical gaps persist in addressing weak-grid conditions at the transmission level. A large proportion of existing studies focus primarily on economic or reliability objectives, while failing to simultaneously incorporate system strength, voltage-stability margins, and life-cycle carbon footprint within a unified optimization framework. Moreover, Weak-grid conditions with high inverter-based resource (IBR) penetration are seldom addressed using explicit system-strength metrics, such as the short-circuit ratio (SCR), as an optimization criterion. In most existing studies, the SCR is evaluated only post-allocation of IBRs to assess grid stiffness, rather than being directly incorporated into the planning or sizing optimization process alongside FVSI-based voltage-stability screening under stochastic RES and load variations. In addition, probabilistic power flow remains underutilized in transmission-level HESS planning, with many studies relying on deterministic formulations or limited scenario-based analyses that inadequately represent the joint uncertainty of wind, solar irradiance, and demand. Finally, although hybrid metaheuristics have gained attention for solving

complex planning problems, they are often applied without a clear problem–algorithm alignment and with excessive parameterization, which can undermine reproducibility, transparency, and convergence robustness.

Motivated by the identified research gaps, this paper presents a comprehensive probabilistic planning framework for the integration of hybrid WTG–PV–HESS systems in weak transmission networks. The proposed approach formulates a weighted-sum multi-objective optimization problem that simultaneously minimizes life-cycle carbon footprint and active power losses, while explicitly enforcing FVSI-based voltage-stability limits and system-strength (SSI) constraints at inverter-based resource connection buses. To rigorously account for uncertainty, a Monte Carlo-based stochastic modeling framework is developed for wind, solar, and load variations and is coupled with probabilistic power flow to assess network performance under realistic operating conditions. The resulting high-dimensional, constraint-driven problem is addressed using a sequential hybrid Whale–Osprey Optimization Algorithm (WOA/OOA), which integrates global exploration and local exploitation to enhance convergence robustness, mitigate premature convergence, and limit the need for extensive parameter tuning. The effectiveness of the proposed framework is demonstrated through a detailed case study on a modified IEEE 39-bus system operating under weak-grid conditions, including comprehensive benchmarking against PSO and GA/PSO-based solution approaches. As summarized in Table 1, existing studies predominantly address RES–storage sizing, stochastic operation, or weak-grid reliability in isolation, whereas integrated probabilistic transmission-level planning frameworks that concurrently enforce system-strength and voltage-stability constraints while optimizing carbon footprint and network losses remain scarce. This identified gap directly motivates both the proposed formulation and the adoption of the sequential WOA/OOA solution strategy.

**Table 1.** Comparison of RES–ESS/HESS Planning Frameworks and Weak-Grid Security Considerations.

| Ref. | Scope/System Level                   | Storage Type                     | Uncertainty Treatment                              | Weak-Grid Strength/Stability Indices                          | Main Objectives                                    | Notes vs. This Work                                                                                     |
|------|--------------------------------------|----------------------------------|----------------------------------------------------|---------------------------------------------------------------|----------------------------------------------------|---------------------------------------------------------------------------------------------------------|
| [12] | Off-grid RES + EV charging           | Hydrogen storage                 | Stochastic sizing (hydrogen + power model)         | Not focused on weak-grid strength metrics                     | Economic/environmental sizing focus                | Not transmission-level; does not enforce SSI/FVSI constraints for weak networks.                        |
| [17] | Standalone PV–wind hybrid (Cameroon) | Battery-based and hydrogen-based | Techno-economic sizing using metaheuristics        | Not formulated around weak-grid SSI/FVSI limits               | Techno-economic optimization                       | Microgrid/standalone focus; does not integrate PPF with SSI/FVSI constraints.                           |
| [22] | Distribution/VPP operation           | EVs + DR within VPP              | Stochastic energy management (Unscented Transform) | Includes operational/voltage security aims (context-specific) | Operation and voltage security objectives          | Operation-centric VPP scheduling; not HESS siting/sizing for weak transmission networks.                |
| [23] | Smart distribution network with VPPs | Renewable-flexible VPPs          | Multi-objective with voltage security index        | Voltage security index included (distribution context)        | Economic operation + voltage security              | Does not address SSI (short-circuit strength) planning at IBR POIs; not HESS planning.                  |
| [24] | Distribution resiliency planning     | VPP placement/sizing             | Extreme events considered (stochastic/resiliency)  | Resiliency constraints emphasized                             | Resiliency-constrained placement and sizing        | Different asset (VPP) and domain (distribution resiliency), not weak-grid SSI/FVSI + HESS.              |
| [26] | Partitioned power networks           | RES + ESS                        | Deterministic allocation in partitioned areas      | Not centered on SSI/FVSI constraints                          | Create supply-sufficient areas/allocation strategy | Network partitioning is different from probabilistic weak-grid security-constrained HESS siting/sizing. |

Table 1. *Cont.*

| Ref.      | Scope/System Level                               | Storage Type | Uncertainty Treatment                                           | Weak-Grid Strength/Stability Indices                | Main Objectives                                        | Notes vs. This Work                                                                                                                        |
|-----------|--------------------------------------------------|--------------|-----------------------------------------------------------------|-----------------------------------------------------|--------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------|
| [27]      | Weak grids (IEEE 39-bus)                         | BESS         | Deterministic planning with SCR screening + reliability indices | SCR screening + voltage/frequency stability metrics | Reliability-driven allocation (EENS, SAIFI, SAIDI)     | Closest in network/weak-grid framing, but does not optimize carbon footprint and does not model RES/load uncertainty via MC-PPF with HESS. |
| This work | Weak transmission network (modified IEEE 39-bus) | HESS         | Monte Carlo-based probabilistic power flow (PPF)                | SSI + FVSI enforced as security constraints         | Weighted-sum minimization of carbon footprint + losses | Integrates uncertainty-aware planning with explicit weak-grid security constraints and HESS sizing/siting.                                 |

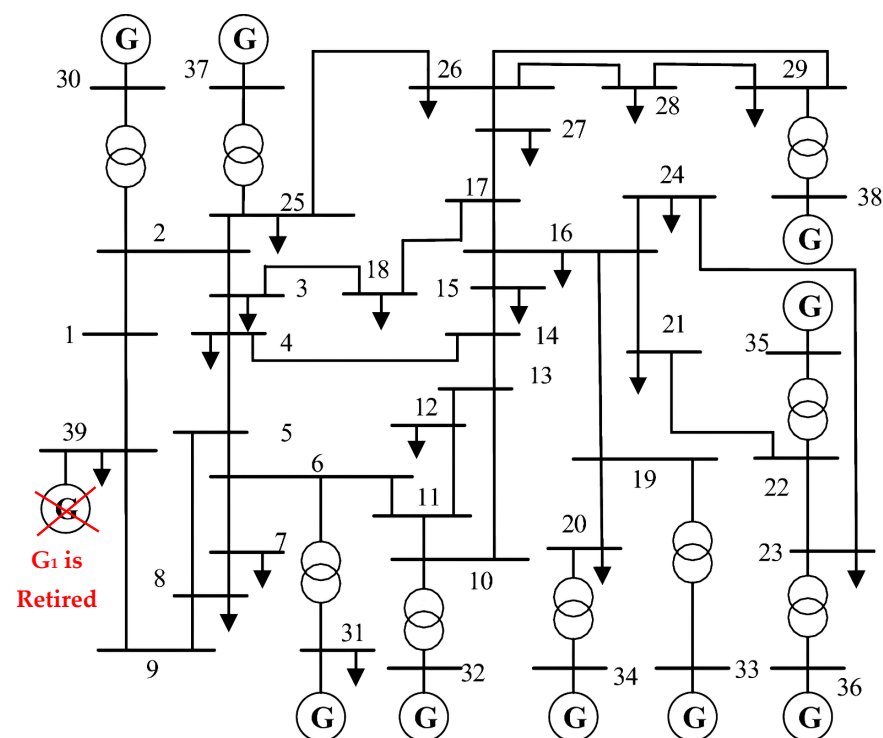
The remainder of this paper is organized as follows: Section 2 presents the modified IEEE 39-bus test system, the investigated RES–HESS integration framework, and the stochastic modeling of wind power, solar irradiance, load demand, and the hydrogen energy storage system. Section 3 formulates the multi-objective optimization problem subject to system security constraints. Section 4 details the proposed optimization methodology and the hybrid WOA–OOA solution strategy. Section 5 provides the simulation results along with a comprehensive comparative analysis. Finally, Section 6 concludes the paper and highlights potential directions for future research.

## 2. Materials and Methods

### 2.1. Case Study Description

The IEEE 39-bus test network, frequently cited as the New England 10-machine system, is one of the most extensively adopted benchmark models in power system research. It represents a reduced-order equivalent of the New England power grid and has become a standard platform for evaluating stability, control strategies, and planning methodologies in large-scale interconnected networks. The network incorporates 39 buses in total, with 19 designated as load buses and 10 functioning as generator buses linked to synchronous units, while the remaining buses function as transmission junctions. The network is interconnected by 46 transmission lines and supported by 12 transformers, which facilitate the linkage between generating units and load centers across different voltage levels. The generators are distributed across the system to realistically capture the operational diversity of a large-scale utility grid. Their rated capacities vary significantly, with some modeled as large thermal generating units and others as equivalent hydro plants, thereby introducing heterogeneity in both active and reactive power contributions. A summary of the maximum generation capacities is provided in Table 2, while comprehensive generator data, including inertia constants and dynamic parameters, can be found in [30]. The total connected load of the system is approximately 6878.1 MW, spatially distributed across multiple buses to reflect realistic consumption patterns. Major load centers are located near the Boston and Connecticut regions in the real-world counterpart, and this spatial distribution has been preserved in the benchmark model to enhance realism. The transmission lines and transformer data of the IEEE 39-bus system are characterized by realistic impedance values, tap-changing ranges, and line charging parameters, as reported in [31]. These details are important for accurately capturing the influence of reactance, resistance, and capacitive charging on both steady-state power flows and system dynamics under disturbances. Complementing these datasets, the load bus specifications summarized in Table 3 present the active and reactive power demand at each bus, thereby establishing the

basis for realistic system operation and performance evaluation. To emulate a weakened grid condition, the benchmark IEEE 39-bus system is modified through the retirement of Generator 1, representing approximately 1000 MW of conventional generation capacity. This modification leads to a measurable reduction in overall system strength, as reflected by the decrease in short-circuit fault levels across the network. In particular, the fault level at Bus 9, identified as the weakest bus in the system, decreases from 2700 MVA<sub>sc</sub> in the original configuration to 2325 MVA<sub>sc</sub> after generator retirement, corresponding to a reduction of approximately 13.9%. This reduction confirms the increase in equivalent network impedance and the deterioration of system strength, thereby establishing a more stressed operating environment that reflects the challenges faced by modern power grids experiencing large-scale renewable integration and the progressive decommissioning of traditional generation assets. The single-line diagram of the modified IEEE 39-bus network is depicted in Figure 1, providing a schematic representation of the system configuration [27]. In this context, the modified network fault level data, presented in Table 4, serves as a critical quantitative indicator of the system's reduced short-circuit strength and validates the weak-grid condition considered in this study.



**Figure 1.** Single-Line Diagram of the Modified IEEE 39-Bus Test System for Power Flow and Stability Studies [27].

**Table 2.** Maximum Generation Capacities of the IEEE 39-Bus Network [30].

| Generator | Connected Bus | Active Power (MW) | Reactive Power (MVAR) | Status  |
|-----------|---------------|-------------------|-----------------------|---------|
| G1        | 39            | 1000              | −36.5                 | Retired |
| G2        | 31            | 571.3             | 363.9                 | ON      |
| G3        | 32            | 650               | 1.5                   | ON      |
| G4        | 33            | 632               | 69.7                  | ON      |
| G5        | 34            | 508               | 148.8                 | ON      |
| G6        | 35            | 650               | 167                   | ON      |

**Table 3.** Active and Reactive Load Demands of the IEEE 39-Bus Network [30].

| Bus Number | P (MW) | Q (MVAR) | Bus Number | P (MW) | Q (MVAR) |
|------------|--------|----------|------------|--------|----------|
| 1          | -      | -        | 21         | 274    | 115      |
| 2          | -      | -        | 22         | -      | -        |
| 3          | 322    | 2.4      | 23         | 247.5  | 84.6     |
| 4          | 500    | 184      | 24         | 308.6  | −92.2    |
| 5          | -      | -        | 25         | 224    | 47.2     |
| 6          | -      | -        | 26         | 139    | 17       |
| 7          | 233.8  | 840      | 27         | 281    | 75.5     |
| 8          | 522    | 176      | 28         | 206    | 27.6     |
| 9          | -      | -        | 29         | 283.5  | 26.9     |
| 10         | -      | -        | 30         | -      | -        |
| 11         | -      | -        | 31         | 9.2    | 4.6      |
| 12         | 7.5    | 88       | 32         | -      | -        |
| 13         | -      | -        | 33         | -      | -        |
| 14         | -      | -        | 34         | -      | -        |
| 15         | 320    | 153      | 35         | -      | -        |
| 16         | 329.4  | 32.3     | 36         | -      | -        |
| 17         | -      | -        | 37         | -      | -        |
| 18         | 158    | 30       | 38         | -      | -        |
| 19         | -      | -        | 39         | 1104   | 250      |
| 20         | 680    | 103      |            |        |          |

**Table 4.** Fault Level Indicators Reflecting System Strength in the Modified IEEE 39-Bus Case.

| Bus Number | Fault Current (kA) | Fault Level (MVA <sub>sc</sub> ) | Bus Number | Fault Current (kA) | Fault Level (MVA <sub>sc</sub> ) |
|------------|--------------------|----------------------------------|------------|--------------------|----------------------------------|
| 1          | 4.67               | 2791.19                          | 21         | 9.45               | 5646.06                          |
| 2          | 12.22              | 7302.96                          | 22         | 9.94               | 5938.73                          |
| 3          | 11.14              | 6658.48                          | 23         | 9.27               | 5537.93                          |
| 4          | 10.03              | 5995.21                          | 24         | 10.40              | 6214.64                          |
| 5          | 9.62               | 5750.05                          | 25         | 10.29              | 6151.13                          |
| 6          | 9.90               | 5917.29                          | 26         | 8.01               | 4785.91                          |
| 7          | 7.81               | 4666.64                          | 27         | 8.10               | 4841.15                          |
| 8          | 7.84               | 4684.54                          | 28         | 4.89               | 2920.73                          |
| 9          | 3.90               | 2329.72                          | 29         | 5.71               | 3415.44                          |
| 10         | 9.38               | 5608.91                          | 30         | 11.44              | 6833.93                          |
| 11         | 9.17               | 5483.54                          | 31         | 8.43               | 5040.77                          |
| 12         | 4.33               | 2585.36                          | 32         | 7.73               | 4621.37                          |
| 13         | 9.03               | 5397.62                          | 33         | 9.48               | 5664.49                          |
| 14         | 9.73               | 5816.56                          | 34         | 7.30               | 4363.28                          |
| 15         | 10.02              | 5986.56                          | 35         | 8.81               | 5265.73                          |
| 16         | 13.89              | 8302.13                          | 36         | 7.18               | 4290.76                          |
| 17         | 12.27              | 7334.41                          | 37         | 7.80               | 4663.34                          |
| 18         | 10.28              | 6142.79                          | 38         | 6.24               | 3728.89                          |
| 19         | 10.23              | 6114.62                          | 39         | 4.22               | 2520.51                          |
| 20         | 7.88               | 4707.74                          |            |                    |                                  |

These values are particularly significant for assessing the System Strength Index (SSI), which provides a quantitative measure of grid robustness under renewable-dominated operating conditions. Moreover, they enable a clear evaluation of the extent to which system strength is reduced following the retirement of conventional generation capacity, thereby capturing the implications of weak grid scenarios.

## 2.2. Stochastic Modeling of RES and HESS

Building on the validated IEEE 39-bus network representation, the study advances toward the deployment of variable renewable generation and hydrogen-based storage technologies. The stochastic nature of solar irradiance, wind speed, and load demand introduces inherent uncertainties that significantly affect system operation, particularly in weak grid conditions. To address these challenges, a hydrogen-based energy storage system (HESS) is incorporated, consisting of electrolyzers, hydrogen storage tanks, and fuel cells, which collectively enable bidirectional energy conversion. This configuration provides a strategic mechanism to absorb surplus renewable generation and compensate for shortfalls, thereby mitigating power imbalances and enhancing overall system resilience. The subsequent sections detail the probabilistic modeling of renewable resources and demand, the dynamic representation of HESS, and the formulation of power mismatch, highlighting the compensating role of HESS in maintaining operational reliability under fluctuating grid conditions.

### 2.2.1. Wind Energy Modeling

Wind speed variability is inherently stochastic and is widely represented through the Weibull probability density function (PDF), owing to its flexibility in modeling diverse wind regimes across geographical and temporal scales.

In this study, the Weibull distribution is adopted to characterize wind speed over the analysis horizon, forming the statistical basis for wind energy generation modeling. The PDF of wind speed  $v^t(t)$  (m/s) at time interval  $t$  is expressed as [32]:

$$f_v(v^t) = \frac{k^t}{c^t} \times \left(\frac{v^t}{c^t}\right)^{k^t-1} \times \exp\left(-\left(\frac{v^t}{c^t}\right)^{k^t}\right) \quad (1)$$

$k^t$  and  $c^t$  represent the shape and scale parameters of the Weibull probability density function, respectively, subject to the conditions  $c^t > 1$  and  $k^t > 0$ . These parameters are typically derived from historical wind speed data. In this study, the shape factor is estimated from the relationship between the statistical mean and standard deviation of the recorded wind data, ensuring that the probabilistic model accurately captures wind resource variability, with the shape factor given by:

$$k^t = \left(\frac{\sigma^t}{\mu_v^t}\right)^{-1.086} \quad (2)$$

and the scale factor by:

$$c^t = \frac{\mu_v^t}{\Gamma\left(1 + \frac{1}{k^t}\right)} \quad (3)$$

where  $\mu_v^t$  and  $\sigma^t$  are the mean and standard deviation of wind speed, and the Gamma function is represented by  $\Gamma(\cdot)$ . The power output of a wind turbine is then modeled using its characteristic power curve [33]:

$$P_w(v_t) = \begin{cases} 0 & v_t \leq v_{cut\ in} \\ \frac{1}{2}C_p\rho Av_t^3 & v_{cut\ in} \leq v_t \leq v_r \\ P_m & v_r \leq v_t \leq v_{cut\ off} \\ 0 & v_t \geq v_{cut\ off} \end{cases} \quad (4)$$

where  $C_p$  is the power coefficient,  $\rho$  is the air density,  $A$  is the rotor swept area, and  $P_m$  is the wind turbine rated power. In this study, wind speed is assumed to follow  $\mu = 8$  m/s and  $\sigma = 1.2$  m/s. To capture uncertainty, Monte Carlo Simulation (MCS) is applied to

generate random wind speed scenarios from the Weibull distribution, enabling probabilistic assessment of wind power availability and its impact on system performance.

### 2.2.2. Solar Energy Modelling

The stochastic nature of solar irradiance necessitates probabilistic approaches for accurately modeling photovoltaic (PV) generation. Solar irradiance is influenced by meteorological and atmospheric factors such as cloud cover, humidity, aerosols, and diurnal cycles, leading to significant temporal and spatial variability. Deterministic models often fail to capture this variability, whereas probabilistic methods provide a more realistic basis for system planning, operational reliability, and resource assessment. Among available distributions, the Beta distribution is particularly suitable due to its bounded support on  $[0, 1]$  and flexible shape characteristics, which allow it to represent the non-Gaussian and often skewed profiles of normalized irradiance data. The probability density function is expressed as [34]:

$$f(x; \alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} * x^{\alpha-1}(1-x)^{\beta-1} \text{ for } 0 < x < 1 \quad (5)$$

$$\alpha = \mu \left[ \left( \frac{\mu(1-\mu)}{\sigma^2} \right) - 1 \right] \quad (6)$$

$$\beta = (1 - \mu) \left[ \left( \frac{\mu(1-\mu)}{\sigma^2} \right) - 1 \right] \quad (7)$$

with  $\mu$  and  $\sigma^2$  denoting the mean and variance of normalized irradiance.

The PV power output is then modeled as:

$$P_{PV}(t) = \eta A_{PV} I_t \quad (8)$$

where  $\eta$  is the overall system efficiency,  $A_{PV}$  is the effective array area, and  $I_t$  is the irradiance at time  $t$ . By integrating the Beta distribution with Monte Carlo simulations, synthetic irradiance and corresponding PV output scenarios can be generated, enabling probabilistic analysis of solar variability, its contribution to the energy mix, and its impact on grid flexibility and reserve requirements.

### 2.2.3. Load Probabilistic Modeling

In large-scale power systems, the electrical load at the transmission level represents the aggregated demand of residential, commercial, and industrial consumers. Owing to this aggregation, random variations in individual loads tend to average out, producing smoother profiles that can be effectively represented by a Normal (Gaussian) distribution. This decision is supported by the Central Limit Theorem, which establishes that the combined effect of a large number of independent random variables asymptotically follows a Gaussian distribution, as well as by empirical evidence from historical load data reported by Transmission System Operators (TSOs).

Accordingly, the load at time  $t$ , denoted by  $L_t$ , is modeled as a normally distributed random variable:

$$L_t \sim N(\mu_t, \sigma_t^2) \quad (9)$$

where  $\mu_t$  and  $\sigma_t^2$  are the mean and variance of load at time  $t$ . The corresponding probability density function is expressed as [35]:

$$f_L(l) = \frac{1}{\sigma_t \sqrt{2\pi}} \exp\left(-\frac{(l - \mu_t)^2}{2\sigma_t^2}\right) \quad (10)$$

The parameters  $\mu_t$  and  $\sigma_t$  can be obtained from historical SCADA or energy management system (EMS) data, using:

$$\mu_t = \frac{1}{N} \sum_{i=1}^N L_t^{(i)} \quad (11)$$

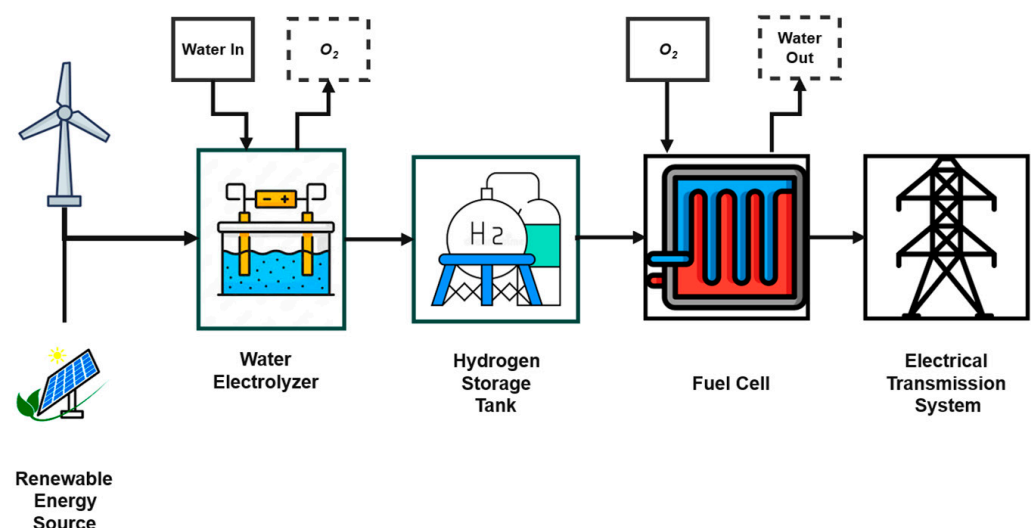
$$\sigma_t = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (L_t^{(i)} - \mu_t)^2} \quad (12)$$

where  $L_t^{(i)}$  is the observed load at time  $t$  on day  $i$ , and  $N$  is the number of days in the dataset. Seasonal and day-type variations (e.g., summer vs. winter, weekday vs. weekend) can be incorporated by estimating these parameters separately for each class.

#### 2.2.4. Green Hydrogen Energy Storage System

The transition toward low-carbon power systems has positioned hydrogen as a strategic energy vector capable of supporting long-duration storage, enhancing grid flexibility, and enabling deep decarbonization. Among its many applications, the Hydrogen Energy Storage System (HESS) is particularly well suited for complementing variable renewable energy sources (RES), such as wind and solar, whose intermittent and non-dispatchable characteristics challenge grid stability.

A typical HESS consists of three key components: a water electrolyzer, a hydrogen storage unit, and a fuel cell as illustrated in Figure 2. During periods of surplus renewable generation, the electrolyzer converts excess electricity into hydrogen by splitting water into hydrogen ( $H_2$ ) and oxygen ( $O_2$ ). The produced hydrogen is then stored under controlled conditions—either at low pressure for short-term applications or at higher pressures (up to 200 bar) for long-term storage [36]. When renewable generation falls below the required dispatch level, the stored hydrogen is reconverted into electricity through a fuel cell, with water vapor as the only byproduct. This closed-cycle operation allows HESS to balance short-term fluctuations, provide seasonal storage, and supply carbon-free dispatchable power, thereby improving the resilience and sustainability of modern grids.



**Figure 2.** Schematic Representation of a Green Hydrogen Energy Storage System (HESS).

In this study, a simplified single-tank configuration operating at a moderate pressure of 30 bar is adopted. This design offers a practical compromise between energy density, operational safety, and system complexity, making it suitable for medium-scale, grid-connected applications. More advanced configurations, such as two-stage storage

with compressors, can reduce energy overheads, but are not considered here to maintain modeling tractability [37].

The electrolyzer operation is governed by the balance between available renewable power and the demand power:

$$P_{ch}(t) = P_{RES}(t) - P_{demand}(t) \quad (13)$$

$$P_{elz} = \frac{\max(P_{ch}(t))}{\varphi \times \eta_{elz}} \quad (14)$$

where  $P_{RES}(t)$  is the real-time renewable energy generation,  $P_{demand}(t)$  the demand power,  $P_{elz}$  the rated electrolyzer capacity,  $\varphi$  the load regulation factor, and  $\eta_{elz}$  the electrolyzer efficiency (typically ~75%). In this study,  $\varphi$  is conservatively set to 1.0, ensuring safe operation under normal conditions.

The fuel cell (FC) is activated when renewable generation is insufficient to meet the dispatch power. The deficit power is:

$$P_{dch}(t) = P_{demand}(t) - P_{RES} \quad (15)$$

The required fuel cell capacity is then:

$$P_{fc} = \frac{\max(P_{dch}(t))}{\eta_{fc}} \quad (16)$$

This ensures the FC can cover the peak deficit while accounting for conversion losses. A Proton Exchange Membrane Fuel Cell (PEMFC) is employed in this study, given its high efficiency, fast dynamic response, and suitability for renewable integration.

The hydrogen tank stores the chemical energy equivalent of the produced hydrogen. The stored energy at time  $t$ , denoted as  $HT_e(t)$ , evolves according to:

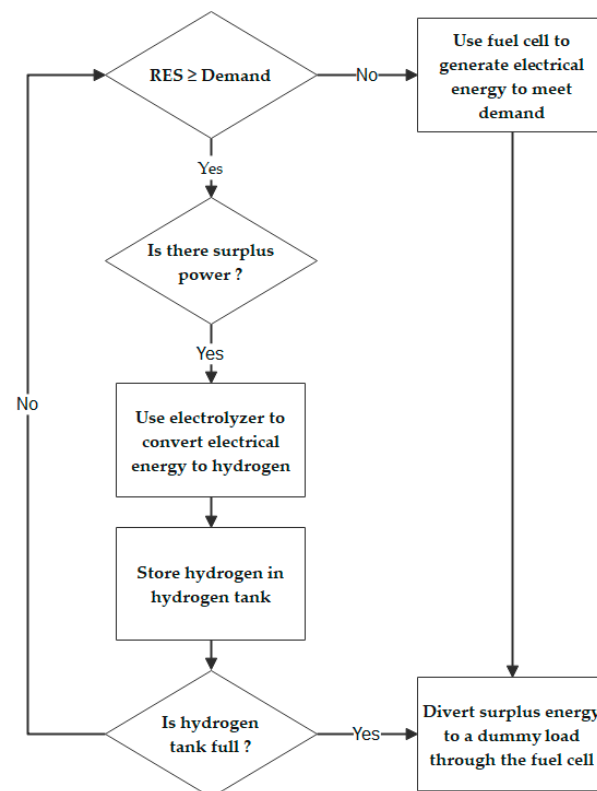
$$HT_e(t) = \begin{cases} HT_e(t-1) - \left( \left( \frac{P_{FC}(t)}{\eta_{fc}} \right) \times \Delta t \right), & P_{RES}(t) < P_{demand}(t) \\ HT_e(t-1) + (P_{elz}(t) \times \eta_{elz} \times \Delta t), & P_{RES}(t) > P_{demand}(t) \end{cases} \quad (17)$$

The corresponding stored hydrogen mass is:

$$HT_m(t) = \frac{\max(HT_e) - \min(HT_e(t))}{(SOC_{max} - SOC_{min}) * HHV} \quad (18)$$

where  $\eta_{fc}$  is the fuel cell efficiency (~60%),  $\Delta t$  is the simulation step (1 h), and HHV is the higher heating value of hydrogen (39.7 kWh/kg). Maximum and minimum tank capacities ( $SOC_{max}$ ,  $SOC_{min}$ ) impose operational boundaries to prevent overcharging or depletion.

The operational framework of RES–HESS is illustrated in Figure 3. If RES generation exceeds demand, surplus energy is directed to the electrolyzer; if demand exceeds RES output, the FC supplies the deficit. When the hydrogen tank reaches full capacity, excess energy is curtailed or diverted to a dummy load. This logic ensures optimized renewable utilization, stable operation of HESS, and effective power balancing [38].



**Figure 3.** Energy Management Workflow for the Operation of a Renewable Energy System (RES) Integrated with Hydrogen Energy Storage System (HESS).

### 3. Multi-Objective Problem Formulation Under System Security Constraints

In multi-objective optimization problems, it is often necessary to balance competing goals within a single framework. In this study, two objectives are considered simultaneously: minimizing the carbon footprint of system generation and reducing active power losses. To enable the joint optimization of these objectives, a scalarization technique based on weighting factors is employed. The overall objective function is expressed as:

$$\text{minimize } (F) = w_1 F_1 + w_2 F_2 \quad (19)$$

where  $F_1$  represents the normalized carbon footprint,  $F_2$  represents the normalized active power loss, and  $w_1$  and  $w_2$  are the respective weighting factors assigned to each objective. The constraint  $w_1 + w_2 = 1$  ensures that the combined function preserves proportional trade-offs between the two terms. The use of weighting factors provides a flexible mechanism to emphasize one objective over the other depending on planning priorities. For example, assigning a higher value to  $w_1$  would prioritize environmental benefits, potentially at the expense of increased power losses. Conversely, a larger  $w_2$  would emphasize network efficiency while tolerating a relatively higher carbon footprint. Such flexibility is essential in real-world power system applications where planners and policymakers may have different preferences depending on policy directives, grid reliability requirements, or carbon reduction targets. In this work, equal weights ( $w_1 = w_2 = 0.5$ ) are selected to assign balanced importance to both objectives. This choice ensures that the optimization framework does not bias the solution toward environmental or technical considerations but instead seeks a compromise that reflects both sustainability and operational efficiency. The equal weighting strategy is also justified by the fact that carbon reduction and power loss minimization are equally critical in achieving resilient and low-carbon grids. Moreover,

equal weights prevent overemphasis on one objective that could potentially drive solutions into technically infeasible or environmentally unsustainable regions. By integrating the weighting factors into the hybrid WOA–OOA optimization, the framework ensures systematic trade-off handling during the search process. The hybrid algorithm explores diverse candidate solutions while continuously evaluating the composite weighted objective, thereby converging toward solutions that provide an optimal balance between emission reduction and loss minimization under the imposed FVSI and SSI constraints.  $F_1$  is Carbon Footprint:

$$F_1 = \frac{LCCF_{conv} \times P_{conv} + LCCF_{RES} \times P_{RES}}{(LCCF_{conv} \times P_{conv})_0} \quad (20)$$

where  $LCCF$  denotes the life-cycle carbon footprint,  $P_{conv}$  and  $P_{RES}$  are the respective power contributions, and the denominator represents the baseline (pre-RES integration).

$F_2$  is Active Power Loss:

$$F_2 = \frac{\sqrt{(\sum_{i=1}^{nb} \frac{P_i^2 + Q_i^2}{|V_i|^2} \times R_i)^2}}{P_{loss,0}} \quad (21)$$

where  $P_i$  and  $Q_i$  are the active and reactive power injections at bus  $i$ ,  $R_i$  is the line resistance, and  $P_{loss,0}$  is the pre-integration network loss.

The methodological framework, depicted in Figure 4, outlines an integrated process for planning under uncertainty. The workflow commences with a system fault level assessment, followed by a Monte Carlo simulation to propagate the uncertainties of renewable generation and load demand. For each of the  $K$  total samples, a set of stochastic inputs is generated, forming a distinct power injection scenario for a given candidate solution. These scenarios inform the generation of an initial population of candidate RES allocations. Each candidate solution is evaluated by solving a Monte Carlo-based Probabilistic Power Flow (PPF). This involves solving the deterministic AC power flow equations for each scenario  $k$ . The power balance equations for a single scenario are given by:

$$\Delta P_i(k) = P_i^{inj,(k)} - V_i^{(k)} \sum_{j=1}^{N_b} V_j^{(k)} (G_{ij} \cos \theta_{ij}^{(k)} + B_{ij} \sin \theta_{ij}^{(k)}) = 0 \quad (22)$$

$$\Delta Q_i(k) = Q_i^{inj,(k)} - V_i^{(k)} \sum_{j=1}^{N_b} V_j^{(k)} (G_{ij} \sin \theta_{ij}^{(k)} - B_{ij} \cos \theta_{ij}^{(k)}) = 0 \quad (23)$$

In these equations,  $P_i^{inj,(k)}$  and  $Q_i^{inj,(k)}$  are the net active and reactive power injection at bus  $i$  for scenario  $k$ , which includes the stochastic renewable generation and load. The variables  $V_i^{(k)}$  and  $\theta_i^{(k)}$  are the voltage magnitude and angle at bus  $i$  for scenario  $k$ ,  $\theta_{ij}^{(k)} = \theta_i^{(k)} - \theta_j^{(k)}$  is the angle difference,  $G_{ij} + jB_{ij}$  is the  $(i,j)$ -th element of the bus admittance matrix, and  $N_b$  is the total number of buses. Solving this system for all  $K$  scenarios yields the probabilistic distributions of the state variables. The optimization process is governed by a set of operational constraints that ensure secure and reliable system performance. The power flow solution for each candidate must adhere to the following limits. Voltage quality is preserved through the enforcement of bus voltage limits:

$$V_{min} \leq V_i \leq V_{max} \quad (24)$$

with  $V_{min} = 0.9$  p.u. and  $V_{max} = 1.1$  p.u. to maintain acceptable operating margins. In addition, system strength requirements are incorporated through the short-circuit ratio constraint as [39].

$$SCR_i \geq 3 \quad (25)$$

where the Short Circuit Ratio (SCR) is defined:

$$SCR_i = \frac{MVA_{sc}}{P_{IBR}} \quad (26)$$

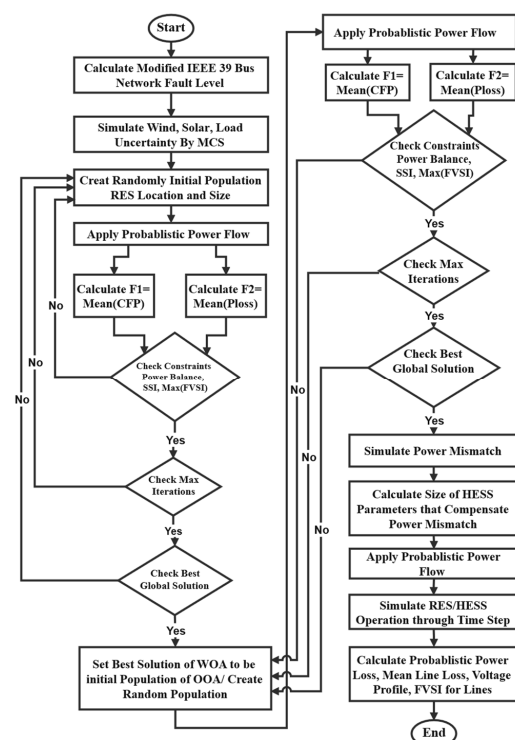
with  $MVA_{sc}$  representing the short-circuit capacity of the bus and  $P_{IBR}$  denoting the rated active power of the inverter-based resource connected at that bus. This condition ensures that the network location provides sufficient short-circuit strength for reliable operation of inverter-based resources. Finally, voltage stability is safeguarded by restricting the Fast Voltage Stability Index (FVSI) according to [40]:

$$\max(FVSI_i) < 1 \quad (27)$$

where Line fast voltage stability index (FVSI) is defined as:

$$FVSI = \frac{4Z_{ij}^2 Q_j}{V_i^2 X_{ij}} \quad (28)$$

where  $FVSI_{ij}$  represents the stability index of line  $i-j$ ,  $Z_{ij}$  is the impedance magnitude of the transmission line, and  $X_{ij}$  denotes the corresponding reactance. The parameter  $Q_j$  refers to the reactive power demand at the receiving bus  $j$ , while  $V_i$  is the voltage magnitude at the sending bus  $i$ . This index is widely used to assess proximity to voltage instability and identify weak lines within the network. Key output statistics from the PPF, such as the expected bus voltage  $E[V_i]$  and its variance  $\text{Var}(V_i)$ , are computed from the ensemble of solutions. These statistics guide the iterative search of the hybrid WOA–OOA algorithm. Upon convergence, power mismatches are quantified, HESS parameters are determined, and the coordinated RES–HESS operation is simulated, with final PPF evaluations yielding comprehensive probabilistic performance measures.



**Figure 4.** Flowchart of the proposed optimization methodology, outlining the sequential process of uncertainty modeling, power flow analysis, and solution search using the hybrid WOA–OOA algorithm.

#### 4. The Proposed Optimization Methodology

The proposed methodology is implemented on the IEEE 39-bus transmission test system, modified by retiring the synchronous generator connected at bus 39. This modification reduces both the available generation capacity and system inertia, thereby creating a more challenging scenario for maintaining voltage stability, system strength, and reliable power balancing. Such a configuration provides a realistic and rigorous case study for evaluating the effectiveness of the optimization framework in addressing renewable energy integration and hydrogen-based energy storage planning under stressed network conditions. To determine the optimal placement and sizing of hydrogen-based energy storage systems (HESs), a hybrid metaheuristic optimization approach is developed by combining the Whale Optimization Algorithm (WOA) and the Osprey Optimization Algorithm (OOA). The hybridization exploits the global exploration capability of WOA and the refined local exploitation capacity of OOA, resulting in a more robust optimization process.

The Whale Optimization Algorithm is inspired by the bubble-net hunting strategy of humpback whales, which can be mathematically expressed through two primary mechanisms: encircling prey and spiral bubble-net feeding. In the encircling mechanism, whales are assumed to estimate the position of their target and gradually converge toward it. The corresponding position update is expressed as [41]:

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)| \quad (29)$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (30)$$

where  $X^*(t)$  denotes the current best solution (prey position),  $X(t)$  is the position of a whale, and  $A$  and  $C$  are coefficient vectors defined as:

$$\vec{A} = 2a \cdot r1 - a, \quad \vec{C} = 2 \cdot r2 \quad (31)$$

with  $r1, r2 \sim U(0,1)$  being random vectors, and  $a$  decreasing linearly from 2 to 0 across iterations to balance exploration and exploitation. In addition, WOA incorporates a spiral updating position to simulate the bubble-net hunting behavior, whereby the whale approaches the prey along a logarithmic spiral path:

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) \quad (32)$$

where  $D' = |X^*(t) - X(t)|$ ,  $b$  is a constant defining the spiral shape, and  $l \in [-1,1]$  is a random parameter. WOA alternates probabilistically between encircling and spiral movements, effectively balancing global exploration and local exploitation. The Osprey Optimization Algorithm (OOA) is inspired by the adaptive hunting behavior of ospreys, which involves searching, diving, and capturing prey. It is particularly effective in exploitation within the local search space and operates through two main phases: exploration and exploitation. In the exploration phase, the algorithm updates candidate solutions according to the expression [42]:

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \alpha \cdot (\vec{X}_{rand}(t) - \vec{X}_i(t)) \quad (33)$$

where  $X_{rand}(t)$  represents a randomly selected solution and  $\alpha$  denotes the adaptive exploration factor. In the exploitation phase, the search intensifies around the best-performing regions using the update rule.

$$\vec{X}_i(t+1) = \vec{X}^*(t) + \beta \cdot (\vec{X}_{best}(t) - \vec{X}_i(t)) \quad (34)$$

where  $X^*(t)$  is the global best solution and  $\beta$  is the exploitation coefficient that regulates the convergence intensity. By employing adaptive parameters, OOA maintains a balance between diversification and intensification, thereby enhancing its convergence accuracy and robustness.

#### Hybrid WOA–OOA Optimization Algorithm

In this study, a sequential hybridization strategy is employed. Unlike operator-level hybridization, where algorithms update the population simultaneously with probabilistic switching, the sequential strategy applies WOA and OOA in succession. WOA is executed first, leveraging its strong global exploration ability to diversify the search space. Once this phase is complete, the best solution identified by WOA is transferred as the initialization point for OOA:

$$\vec{X}_{best}^{WOA} \rightarrow \vec{X}_{init}^{OOA} \quad (35)$$

$$\vec{X}_{final} = OOA(\vec{X}_{init}^{OOA}) \quad (36)$$

where  $\vec{X}_{best}^{WOA}$  is the global best solution obtained from WOA, and  $\vec{X}_{final}$  is the refined optimal solution provided by OOA. This sequential hybridization significantly improves convergence speed and solution accuracy by exploiting WOA's exploration capacity and OOA's exploitation refinement. Within the modified IEEE 39-bus system, this approach ensures effective identification of optimal HESS placement and sizing, while adhering to operational constraints and minimizing the defined multi-objective function.

## 5. Results and Discussions

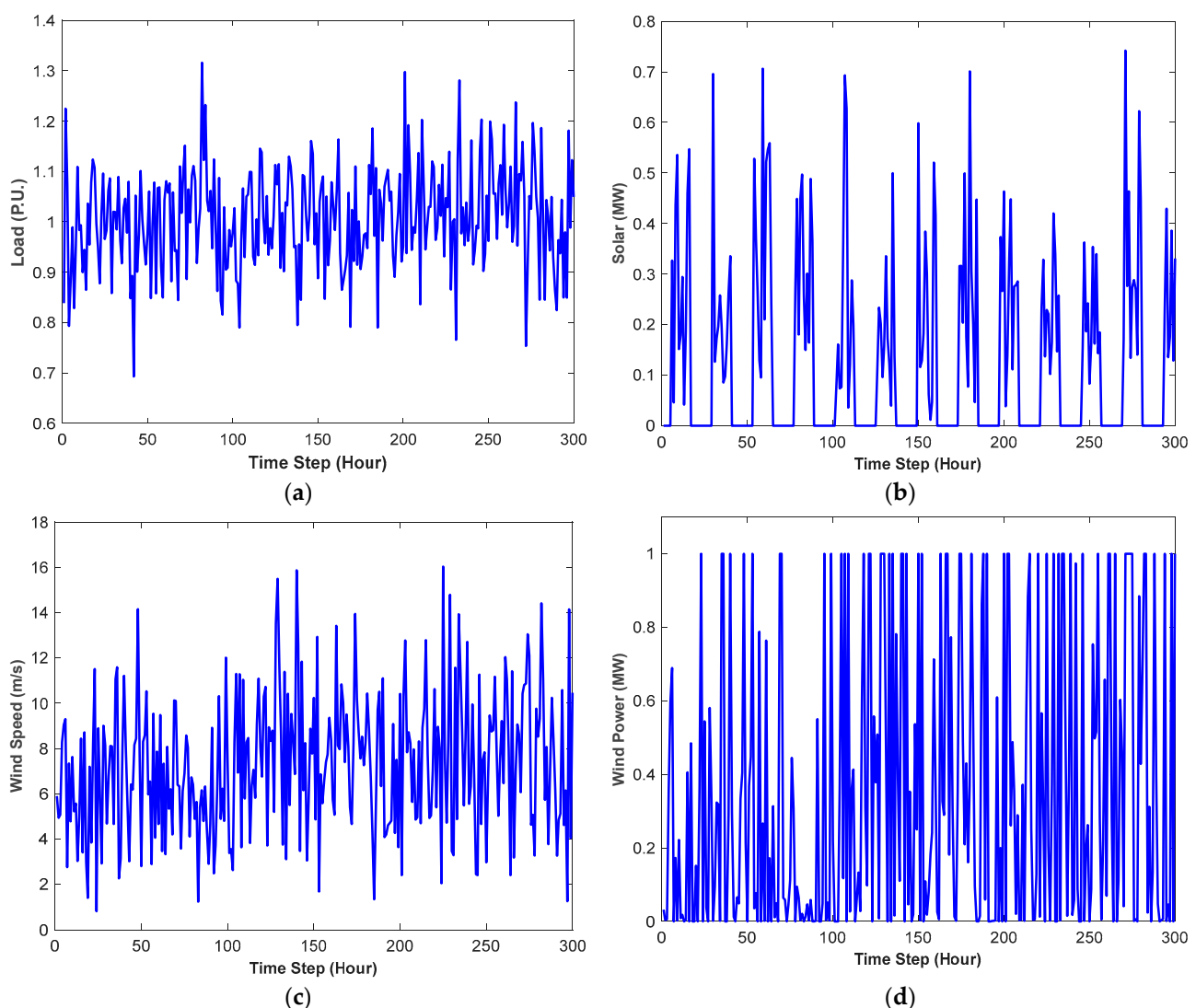
Optimal placement and sizing of RES and HESS are investigated within the IEEE 39-bus system, where the hybrid WOA–OOA algorithm is benchmarked against Particle Swarm Optimization (PSO) to validate its performance. The inclusion of FVSI as a constraint ensures secure operation by preventing instability. Prior to optimization, short-circuit levels at all buses are computed in MATLAB/Simulink R2021b without RES/ESS integration, serving as inputs to calculate the System Strength Index (SSI).

The operational dispatch of wind power is analyzed through Monte Carlo simulations, where wind speed is characterized by a Weibull probability distribution. To evaluate each candidate solution during the optimization process, the power flow is solved using the Newton-Raphson method within the MATPOWER environment. This ensures precise calculation of system objectives and adherence to operational limits. The core objective of this framework is to identify the ideal capacity ratings for the components of a Hydrogen Energy Storage System (HESS), enabling a robust evaluation of its efficacy in stressed network conditions. The adoption of WOA–OOA is motivated by its ability to overcome the limitations of conventional meta-heuristics such as PSO and GA, which often converge prematurely or exhibit reduced efficiency in high-dimensional, nonlinear problems. By combining WOA's strong global exploration capability with OOA's efficient local exploitation, the hybrid algorithm achieves faster convergence, avoids stagnation in local optima, and delivers higher-quality solutions, particularly under the multi-objective and constraint-driven conditions imposed by FVSI and SSI.

### 5.1. Uncertainty Modeling for Wind, Solar and Load

In this study, Monte Carlo Simulation (MCS) is employed to capture the stochastic behavior of load, solar irradiance, and wind speed. A total of 300 Monte Carlo samples are generated, corresponding to a 300 h time horizon, to represent the temporal variability and uncertainty of system operating conditions. The convergence of the probabilistic representation is verified by monitoring the stability of key statistical indicators, including the mean

and variance of load demand and renewable generation profiles. It was observed that these statistical measures stabilized within the selected sample size, confirming the adequacy of 300 samples for reliable probabilistic analysis. The hourly load is modeled as a Gaussian distribution with a mean of 1 MW and variability of  $\pm 0.1$  MW, while solar generation is represented by a Beta distribution ( $\alpha = 2$ ,  $\beta = 5$ ) scaled to 1 MW. Wind speed follows a Weibull distribution (scale = 8, shape = 2.5) and is converted to wind turbine output using standard operating parameters, yielding a 1 MW rated capacity. These generated samples constitute the K probabilistic scenarios used in the probabilistic power flow and optimization framework. A Hydrogen Energy Storage System (HESS) with electrolyzer and fuel cell efficiencies of 0.75 and 0.6, respectively, is integrated to enhance flexibility and reliability. Figure 5 presents the time-series profiles of load demand, solar generation, wind speed, and wind power output over the 300 h horizon, providing a realistic and statistically representative basis for probabilistic analysis in the IEEE 39-bus system.

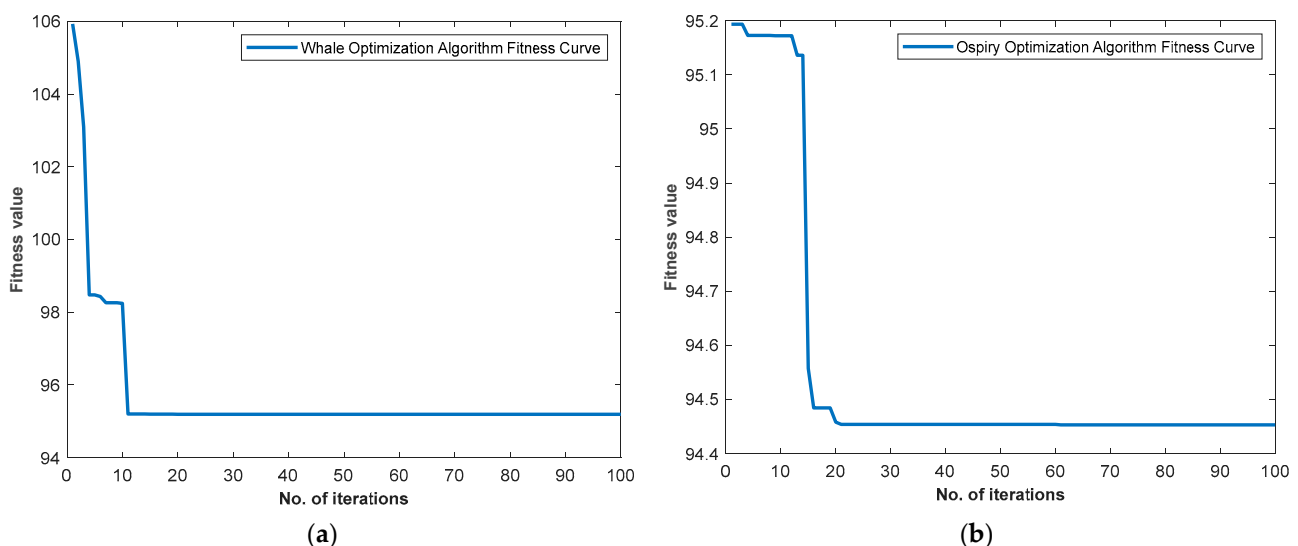


**Figure 5.** Time-series profiles of key input variables over the simulation horizon: (a) load demand, (b) solar generation, (c) wind speed, and (d) corresponding wind power output, illustrating the stochastic variations considered in the probabilistic analysis.

## 5.2. Proposed Optimization Framework Results

As shown in Figure 6a,b, the convergence behavior of the Whale Optimization Algorithm (WOA), Osprey Optimization Algorithm (OOA), and their hybrid clearly demon-

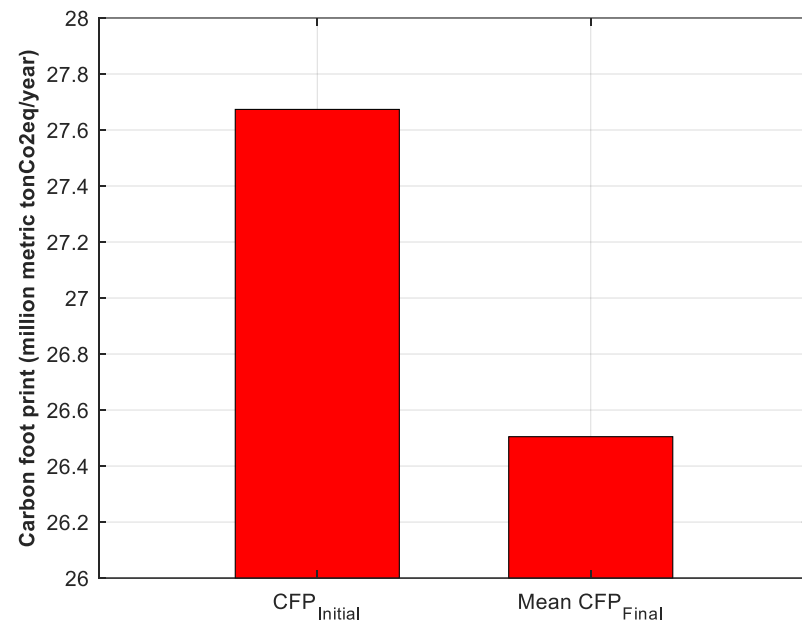
states the advantage of the combined WOA–OOA approach. Whereas the standalone algorithms show slower convergence and a higher tendency to stagnate in local optima, the hybrid algorithm consistently achieves rapid and stable progress toward the global solution. Specifically, Figure 6a shows that the hybrid WOA–OOA converges within approximately 15–20 iterations, while Figure 6b indicates convergence within 20–30 iterations. In contrast, the convergence behavior of Particle Swarm Optimization (PSO) occurs only after 40–50 iterations, while the hybrid PSO/GA requires as many as 80–90 iterations to reach stability. This highlights the markedly faster convergence of the proposed method. The improvement arises from the complementary balance of WOA’s exploration ability and OOA’s exploitation strength, which together ensure both diversity of search and precision of refinement. Such characteristics are especially important in solving nonlinear, uncertain, and multi-objective optimization problems typical of power system planning. Compared with conventional methods like PSO and PSO/GA, which often suffer from premature convergence or prolonged computation under complex constraints, the hybrid WOA–OOA offers superior global search capability, faster convergence, and more reliable solution quality.



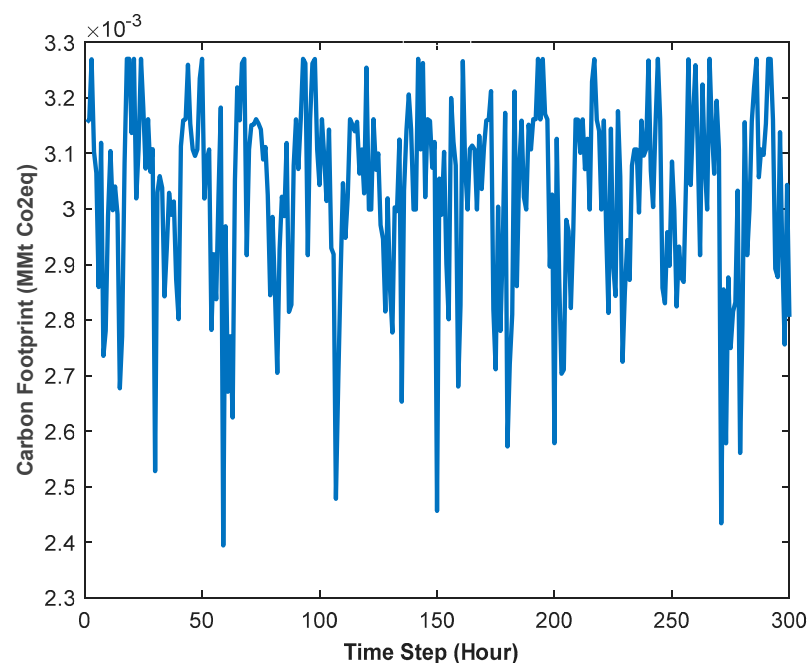
**Figure 6.** Convergence behavior of metaheuristic algorithms: (a) Whale Optimization Algorithm (WOA) and (b) Osprey Optimization Algorithm (OOA), showing their fitness evolution during the optimization process.

Figure 7 further illustrates that the integration of RES and HESS reduces the annual carbon footprint from 27.6 Mt CO<sub>2</sub>eq/yr to 22.16 Mt CO<sub>2</sub>eq/yr, highlighting the effectiveness of the proposed framework in advancing decarbonization. Complementing this outcome, Figure 8 shows the stochastic emission dynamics, where the carbon footprint fluctuates around a mean of 22.6 Mt CO<sub>2</sub>eq/yr with a standard deviation of 2 Mt CO<sub>2</sub>eq/yr. These probabilistic results underscore the essential role of HESS in mitigating emission variability by counteracting renewable intermittency, thereby enhancing both environmental benefits and operational reliability. Beyond carbon footprint reduction, power loss optimization highlights the operational value of the proposed framework. Minimizing active power losses enhances network efficiency, lowers generation requirements, and supports sustainability goals. The integration of RES and HESS is therefore evaluated not only for emission mitigation but also for its impact on transmission losses. Figure 9 shows a marked reduction, with network losses decreasing from 78 MW in the baseline to a mean of 67.68 MW after optimization. Figure 10 presents the stochastic dynamics of losses, fluctuating around a mean of 67.68 MW with a standard deviation of 13.9 MW, reflecting

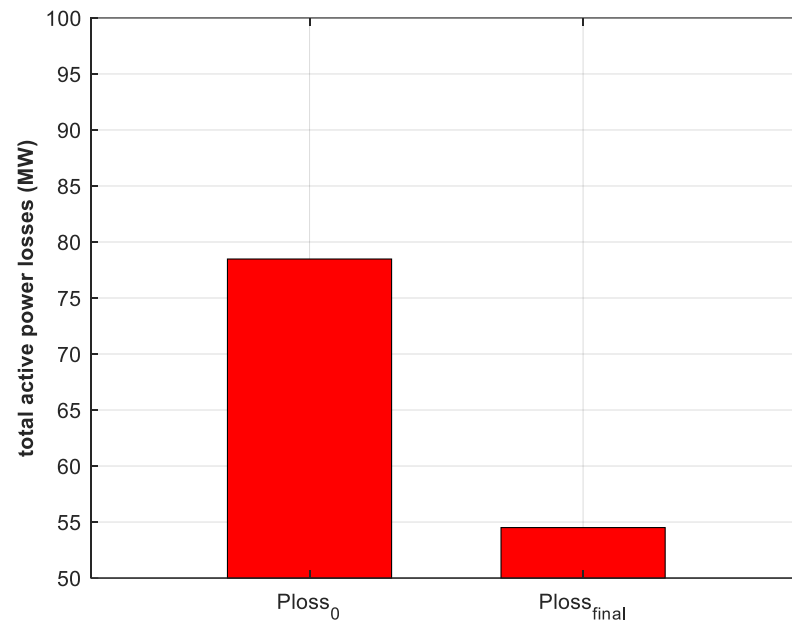
variability under uncertainty. Figure 11 complements these results by showing line-wise reductions, confirming improved efficiency across the transmission network. By enhancing voltage stability and regulation, the proposed framework ensures secure operation under high renewable penetration. The initial voltage profile, with a minimum of 0.88 p.u. and a maximum of 1.05 p.u., indicates a stressed network; post-integration, these extremes are tightened to 0.94 p.u. and 1.045 p.u., as illustrated in Figures 12 and 13. This improvement is corroborated by the Voltage Stability Index (VSI), where both mean and maximum values are reduced, shifting the system toward secure operating margins. The lower mean VSI reflects system-wide stability enhancement, while the reduced maximum VSI mitigates critical vulnerabilities, as shown in Figure 14a,b.



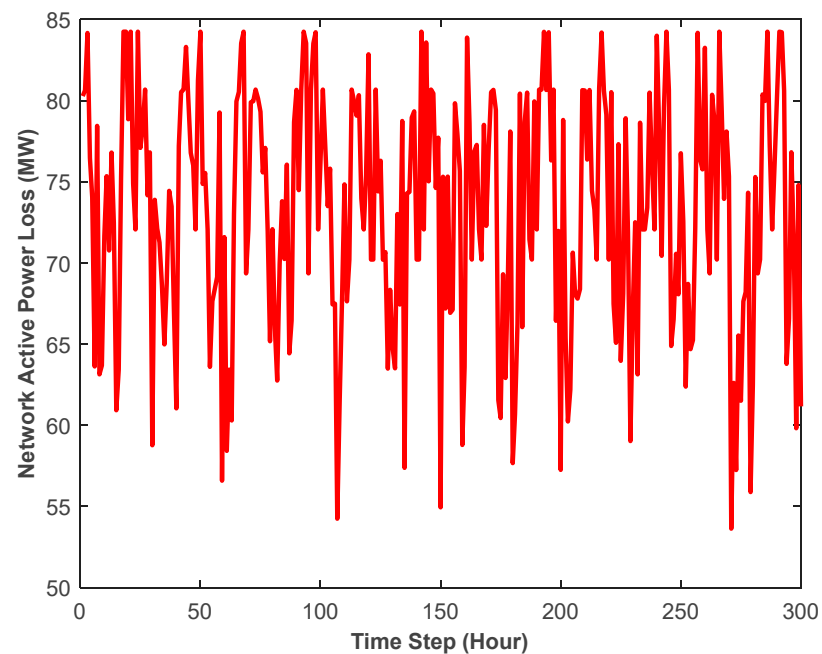
**Figure 7.** Comparison of carbon footprint before RES/HESS integration and after optimization, highlighting the reduction achieved through the proposed framework.



**Figure 8.** Probabilistic variation in the carbon footprint after RES/HESS integration across the simulation horizon, reflecting the influence of renewable intermittency and uncertainty.



**Figure 9.** Comparison of active power losses before RES/HESS integration and after optimization, showing the improvement in network efficiency.

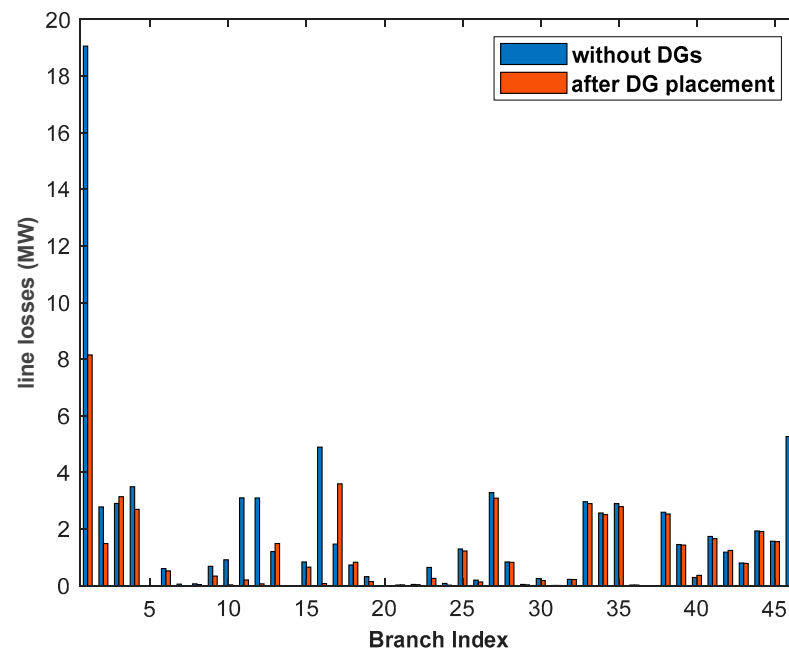


**Figure 10.** Probabilistic variation in active power losses after RES/HESS integration across the simulation horizon, highlighting the impact of uncertainty on network efficiency.

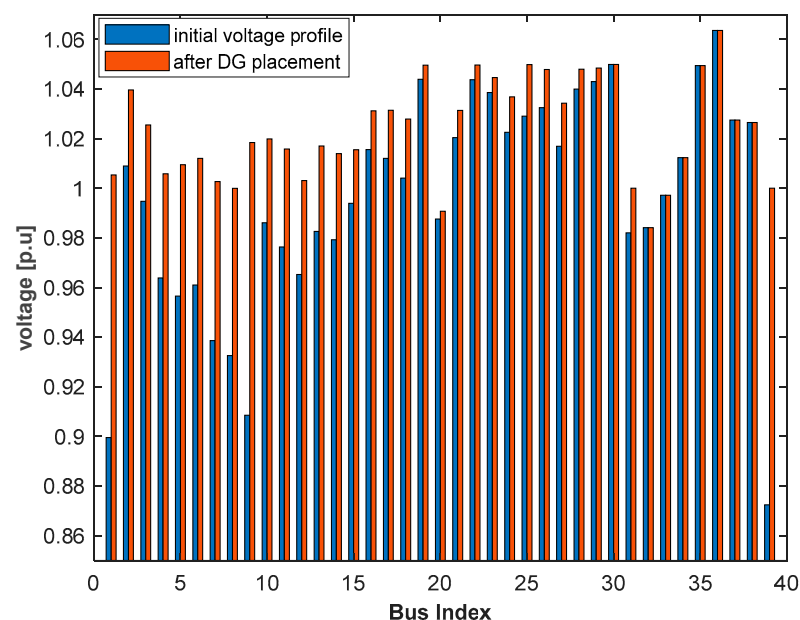
Alternative methods such as PSO or GA/PSO distributed resources differently; however, the hybrid allocation yielded superior SSI margins and minimized power losses. This improvement arises from the strategic placement of RES/HESS at heavily loaded buses, which reduces current flow in critical lines, alleviates congestion, and enhances overall network efficiency. The detailed allocation results for the integration of five RES/ESS plants are provided in Table 5 for further quantitative assessment.

The efficacy of the coordinated renewable energy source and hybrid energy storage system (RES/HESS) integration in mitigating active power imbalances is quantitatively demonstrated in the following analysis. Figure 15a depicts the net active power mismatch attributable to RES generation intermittency, while Figure 15b illustrates the corresponding

power compensation delivered by the HESS. Figure 16a presents the power injected by the fuel cell, which is engineered to offset the aforementioned power mismatch. Complementarily, the state of charge of the hydrogen storage tank, indicative of the available energy buffer throughout the compensation cycle, is shown in Figure 16b.



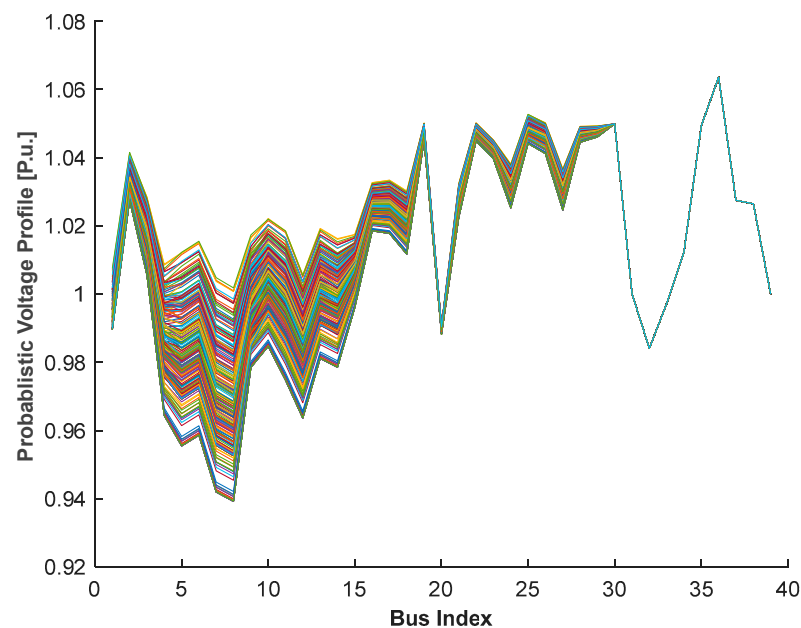
**Figure 11.** Line-wise active power losses of the IEEE 39-bus system before and after RES/HESS integration, showing significant reductions across multiple transmission branches that reflect improved network efficiency.



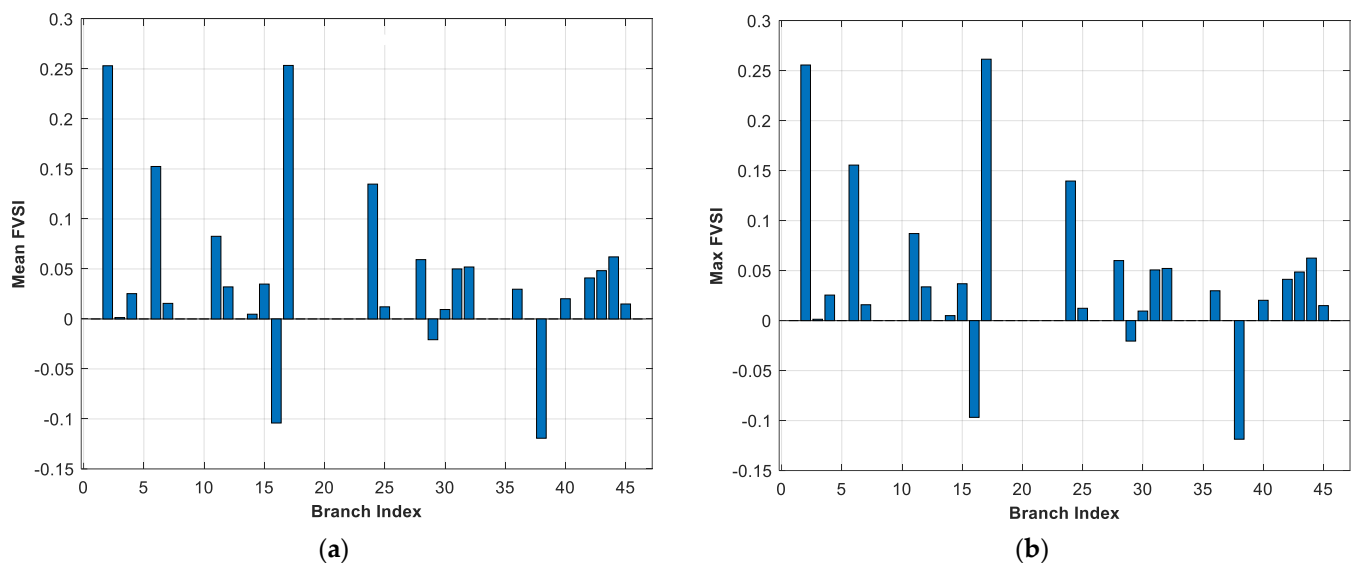
**Figure 12.** Voltage profile of the IEEE 39-bus system before and after RES/HESS integration, highlighting improvements in minimum and maximum bus voltages and enhanced overall voltage regulation.

Furthermore, carbon footprint reduction is achieved as HESS enables higher renewable utilization by storing excess generation and dispatching it during high-demand periods, thereby offsetting fossil-fuel-based generation and mitigating emission variability. Table 4 summarizes the resulting allocations, including bus numbers, RES and HESS capacities,

voltage levels, SSI margins, and power loss reductions for the hybrid method and alternative approaches, clearly demonstrating the operational and environmental benefits of the proposed framework.



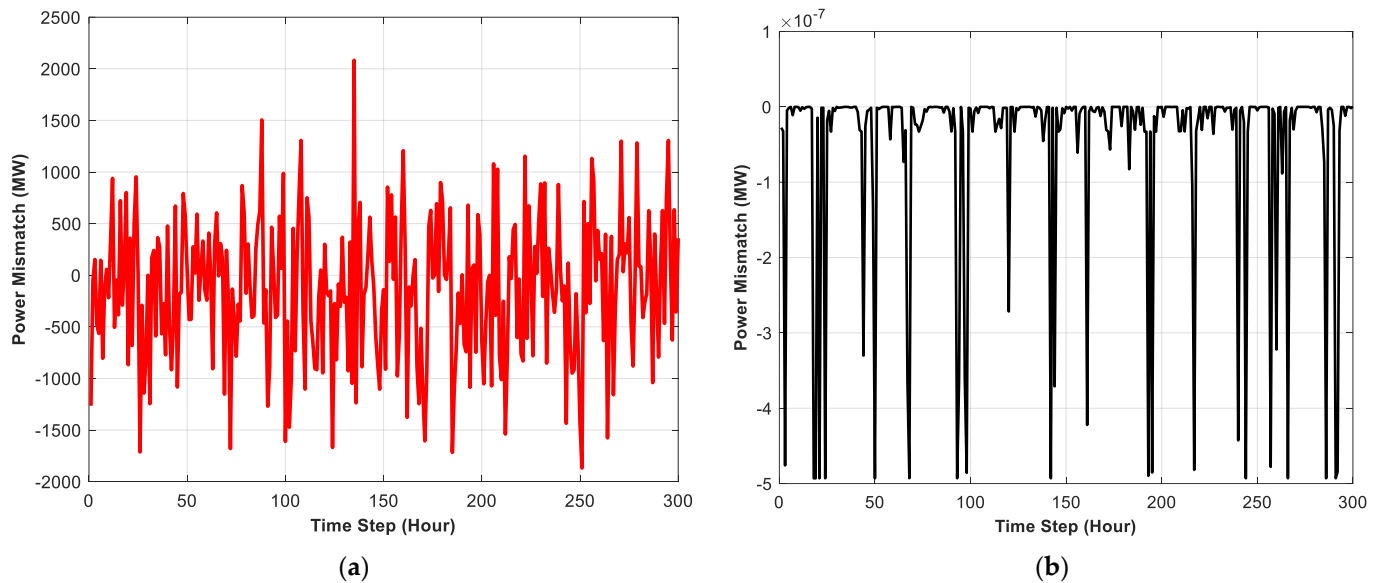
**Figure 13.** Probabilistic voltage profile of the IEEE 39-bus system after RES/HESS integration, illustrating voltage variations across time steps under stochastic operating conditions.



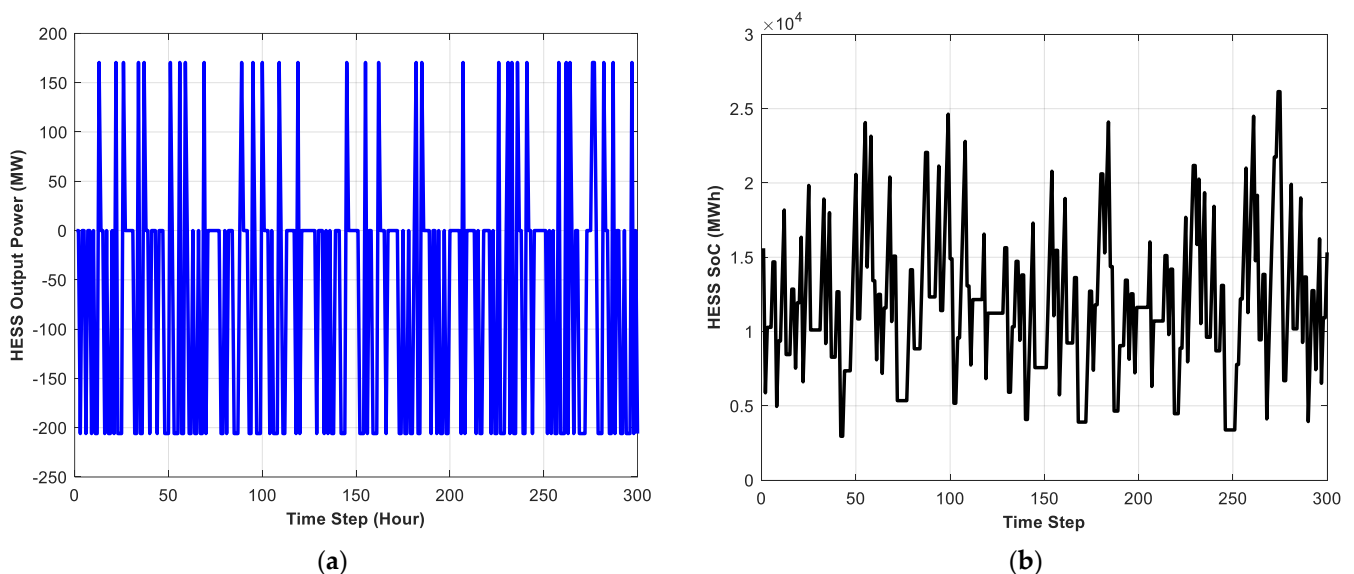
**Figure 14.** Fast Voltage Stability Indices (FVSI) for network branches: (a) mean values reflecting overall system stability and (b) maximum values indicating the most critical branch conditions after RES/HESS integration.

In contrast to the BESS-focused methodology in [27], which assumed 2830 MW of RES penetration and determined an optimal BESS capacity of 284 MVA to maintain grid resiliency using an Adaptive Grey Wolf Optimizer (AGWO) and reliability indices, this study proposes a holistic RES-HESS integration framework that addresses both technical and environmental objectives. While [27] demonstrates improvements in reliability indices such as EENS and SAIFI, our methodology incorporates carbon footprint minimization, loss reduction, and system strength indices (FVSI/SSI) through a hybrid WOA-OOA optimization

coupled with probabilistic Monte Carlo simulation. Notably, the HESS capacity resulting from our optimization, comprising a 297 MW electrolyzer and 263 MW fuel cell, closely aligns with the storage capacity identified in [27], confirming the consistency of storage sizing requirements across different methodological approaches. This convergence underscores the robustness of both methods in determining storage needs for high-RES systems, while our framework extends the scope by integrating decarbonization and multi-technical metrics, offering a more comprehensive planning tool for sustainable power systems.



**Figure 15.** (a) Net active power mismatch before and after Hydrogen Energy Storage System (HESS) integration, showing the mitigation of renewable generation intermittency. (b) Compensation provided by the HESS, demonstrating its effectiveness in balancing supply–demand mismatches and enhancing system reliability.



**Figure 16.** (a) Fuel cell power output of the Hydrogen Energy Storage System (HESS) across time steps, illustrating its compensatory role in offsetting net power mismatches caused by renewable intermittency. (b) State of charge of the hydrogen storage tank, reflecting the dynamic energy buffer available to sustain grid support during operation.

The convergence patterns illustrate that the hybrid WOA–OOA effectively leverages the complementary strengths of its constituent algorithms. By combining WOA’s strong exploration capability with OOA’s precise exploitation, the hybrid method maintains search diversity while efficiently refining solutions toward the global optimum. This synergy reduces the risk of stagnation in local minima and accelerates convergence compared with standalone or conventional hybrid algorithms. Such characteristics make the approach particularly well-suited for complex, nonlinear, and multi-objective optimization problems, as commonly encountered in power system planning, where both computational efficiency and solution reliability are critical.

The results demonstrate that voltage magnitudes remain within acceptable operational limits (typically 0.95–1.05 p.u.) for most buses despite stochastic variations in RES output and load demand. The spread of the profiles reflects the uncertainty introduced by renewable generation; however, the integration of HESS effectively mitigates extreme voltage deviations. Overall, the system maintains satisfactory voltage stability under probabilistic operating scenarios.

As observed in Figure 15a, the system experiences significant active power fluctuations due to renewable intermittency. After integrating the HESS, these deviations are substantially reduced, as shown in Figure 15b, confirming its effectiveness in smoothing power variations and maintaining supply–demand balance. The operational behavior of the HESS is illustrated in Figure 16, where Figure 16a shows the fuel cell power response to mismatch conditions, and Figure 16b presents the hydrogen tank state of charge, highlighting its dynamic energy buffering capability under stochastic operation.

**Table 5.** Allocation Results for the Insertion of Five RES/ESS Plants.

|                                                         | WAO/OOA Optimization | GA/PSO Optimization | PSO Optimization |
|---------------------------------------------------------|----------------------|---------------------|------------------|
| Allocated Buses No.                                     | 7,8,23,31,39         | 4,7,8,9,39          | 6,8,9,31,39      |
| Total RES Capacity (MW)                                 | 2428                 | 4160                | 3699             |
| Total Electrolyzer Capacity (MW)                        | 296.9                | 648.1               | 453.33           |
| Total Fuel Cell Capacity (MW)                           | 262.7                | 186                 | 181.5            |
| H <sub>2</sub> Storage Capacity (kg)                    | 28,012.1             | 49,000.5            | 34,881.7         |
| Weakest Bus Min SSI                                     | 4.68 @ bus 7         | 3.4 @ bus 7         | 3.01 @ bus 9     |
| Mean Network Mean Power Loss (MW)                       | 67.68                | 65.51               | 63.8             |
| STD of Power Loss (MW)                                  | 13.9                 | 10.5                | 11               |
| Mean Network Carbon Footprint (Mt CO <sub>2</sub> e/yr) | 22.16                | 23.4                | 24.4             |
| STD Network Carbon Footprint (Mt CO <sub>2</sub> e/yr)  | 2                    | 3.45                | 2.7              |

## 6. Conclusions

An integrated planning framework for the coordinated deployment of renewable energy sources (RES) and hydrogen-based energy storage systems (HESS) has been presented, addressing variability and reduced system strength in low-carbon power grids. Environmental performance and operational reliability were jointly considered, with probabilistic assessment employed to capture uncertainties. Application to the IEEE 39-bus system demonstrated a reduction in carbon footprint from 27.7 to 22.16 million metric tons of CO<sub>2</sub>eq and a decrease in active power losses from 78 MW to 67.68 MW while maintaining stability with a maximum FVSI of 0.28. The hybrid WOA–OOA optimization method further enhanced performance by leveraging WOA’s exploration and OOA’s exploitation capabilities, thus avoiding premature convergence and improving robustness relative to conventional techniques.

Although the HESS model was simplified for tractability, the framework provides valuable insights for the planning of RES-HESS integration in practical power systems. Future research is recommended to incorporate detailed electrochemical, thermal, and operational dynamics of HESS, as well as to extend the framework to larger-scale networks

and diverse operational scenarios, in order to validate robustness and applicability in sustainable power system planning.

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