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Gathering Before Acting: A Bio-Inspired Perspective on State-of-the-Art Analysis and Prospects for Green Hydrogen Hybrid Systems in Mexico

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Abstract
The successful deployment of green hydrogen systems requires rigorous information acquisition before large-scale capital commitment, analogous to the reconnaissance strategies employed by many animal species prior to resource-intensive actions. This perspective paper examines the state of the art of hybrid renewable energy systems for green hydrogen production through the lens of bio-inspired information-gathering processes. We map natural behaviors—scouting, environmental sampling, risk assessment, and adaptive decision-making—onto the technical pipeline of resource characterization, dynamic electrolyzer modeling, multi-objective Pareto exploration, and uncertainty quantification. Special attention is given to northern Sinaloa, Mexico, a region of high solar–wind complementarity that already hosts concrete project pipelines such as the Tango Solar / DH2 development. The algorithmic foundation rests on multi-objective evolutionary algorithms (NSGA-II, NSGA-III, SPEA2, MOPSO) enhanced by nature-inspired mechanisms such as the Hippopotamus Optimization Algorithm and sexual-selection operators. These methods function as computational reconnaissance tools that explore trade-offs among levelized cost of hydrogen (LCOH), renewable fraction, electrolyzer capacity factor, unused renewable energy, and CO_2 emissions. We conclude with a research agenda that treats information acquisition as a first-class design phase, offering guidance for researchers, developers, and policymakers engaged in Mexico's emerging hydrogen economy.

Keywords: *green hydrogen; hybrid renewable systems; multi-objective optimization; bio-inspired algorithms; Hippopotamus Optimization; NSGA-III; northern Sinaloa; Mexico; information gathering; Pareto front*

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I. Introduction

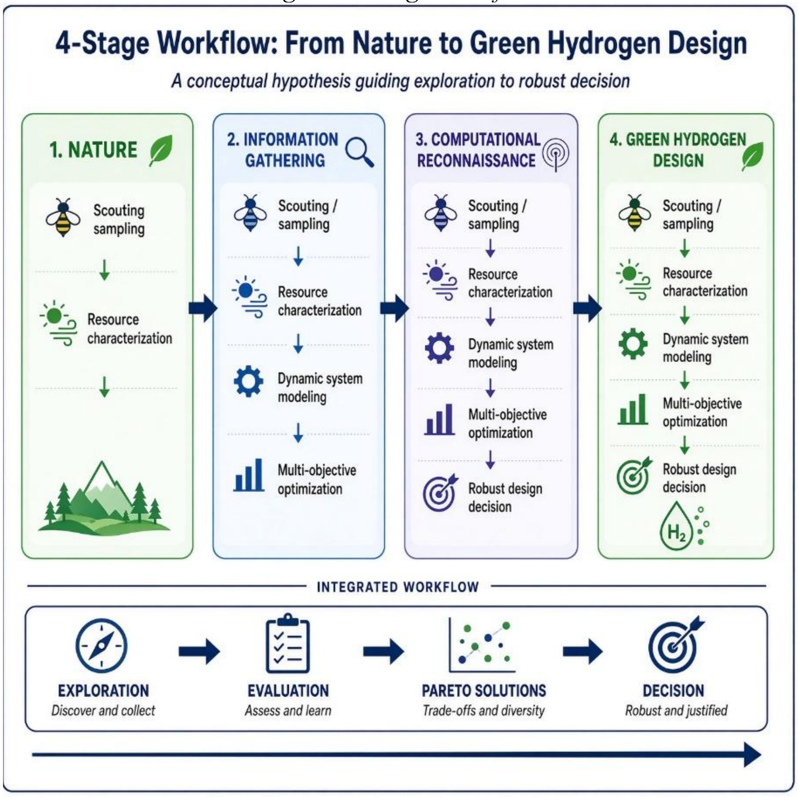
The global transition toward low-carbon energy systems has elevated green hydrogen—produced via water electrolysis powered by renewable electricity—to a central role in decarbonizing hard-to-abate sectors such as heavy industry, long-haul transport, and chemical production [1,2]. Mexico possesses exceptional solar and wind resources, particularly in its northern states, positioning the country as a potential regional leader in green hydrogen. Recent assessments indicate a pipeline of approximately 24–30 projects representing more than US$21–22 billion in potential investment, with projected annual production capacities on the order of 197,000 tonnes of green hydrogen together with substantial volumes of green ammonia and methanol derivatives.

Despite this promise, the technical and economic viability of hybrid renewable–hydrogen systems remains highly sensitive to resource variability, technology selection (alkaline, proton-exchange membrane, or solid-oxide electrolysis), storage architecture, grid interaction, and capital cost trajectories [3,4]. Premature commitment to specific configurations under incomplete information carries substantial financial and operational risk. In nature, many animal species mitigate analogous risks by investing energy in information gathering—scouting, sampling, and risk assessment—before committing to migration, territory defense, or large-scale foraging. This paper adopts that biological principle as a conceptual frame for the design of green hydrogen systems.

We argue that the state-of-the-art analysis of hybrid systems for green hydrogen should be reoriented around systematic reconnaissance: high-resolution characterization of solar–wind complementarity, dynamic modeling of electrolyzer performance under variable load, multi-objective exploration of the Pareto surface, and robust quantification of uncertainty. Northern Sinaloa, with documented project activity (including the Tango

Solar / DH2 development near El Fuerte) and favorable resource conditions, serves as a concrete regional focus. The algorithmic tools capable of performing this reconnaissance are multi-objective evolutionary algorithms, further strengthened by recent nature-inspired methods such as the Hippopotamus Optimization Algorithm [5].

Figure 14 Stage Workflow



II. Information-Gathering Strategies in Animal Decision-Making

Behavioral ecology demonstrates that animals routinely trade short-term energetic costs for information that reduces long-term risk. Scout bees sample floral patches and communicate quality via the waggle dance before the colony allocates foragers. Foraging mammals and birds perform exploratory sampling to estimate resource density and predation risk. Social groups of large mammals, including hippopotamuses, assess water quality, depth, and safety before settling or relocating [5]. In each case, the organism invests in reconnaissance because the cost of acting under high uncertainty exceeds the cost of information acquisition.

These strategies embody a fundamental exploration–exploitation balance. Exploration generates diverse samples of the environment; exploitation capitalizes on the best-evaluated options. The same balance underpins modern multi-objective evolutionary algorithms, which maintain populations of candidate solutions (scouts) and iteratively improve both the quality and the diversity of the non-dominated set (the Pareto front). Framing system design as an information-gathering process therefore provides a principled link between natural intelligence and computational optimization.

III. Mapping Animal Reconnaissance to the Green Hydrogen Design Pipeline

The analogy can be made operational by mapping biological reconnaissance stages onto the engineering workflow:

1. **Environmental sampling** corresponds to the collection and statistical characterization of high-resolution solar irradiance, wind speed, temperature, and complementarity metrics. Complementarity analysis quantifies the degree to which solar and wind resources offset each other's variability, thereby reducing storage requirements [6,7].
2. **System-response understanding** requires dynamic models of electrolyzers that capture efficiency variation with load, start-up and ramp constraints, and degradation. Static models that assume constant efficiency systematically oversize equipment and under-estimate operating costs [3,8].
3. **Strategy-space exploration** is performed by multi-objective optimizers that generate the Pareto front of competing designs. Typical objectives include minimization of levelized cost of hydrogen (LCOH),

maximization of renewable fraction and electrolyzer capacity factor, and minimization of unused renewable energy and life-cycle CO_2 emissions [6,9].

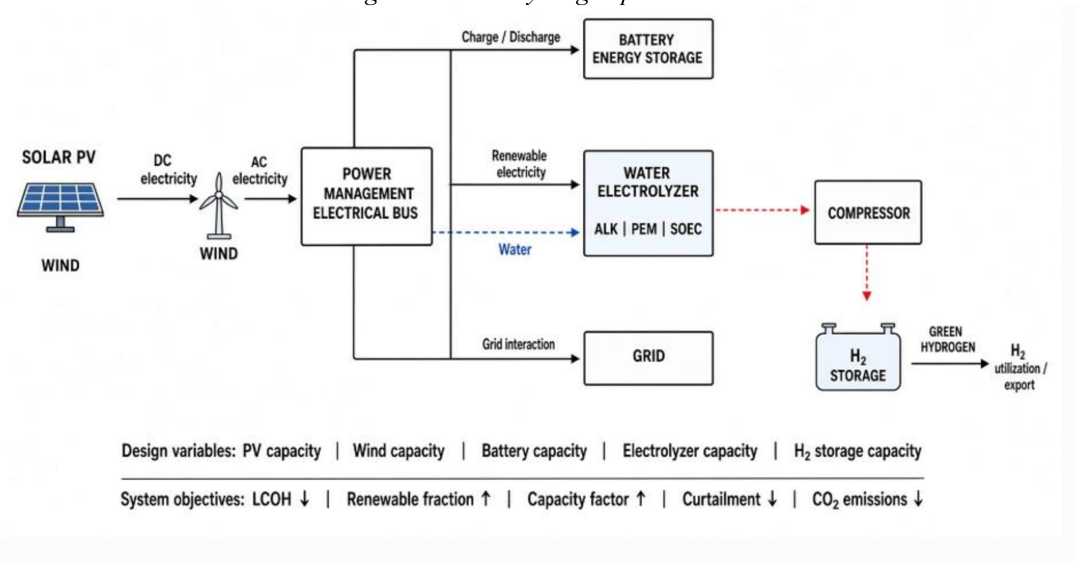
4. **Risk assessment before commitment** consists of parametric sensitivity studies and stochastic simulations that propagate uncertainty in capital costs, resource availability, discount rates, and electricity prices into distributions of LCOH and reliability metrics [4,10].

IV. State-of-the-Art of Hybrid Renewable Systems for Green Hydrogen

4.1 System Architectures and Electrolysis Technologies

Hybrid systems typically integrate photovoltaic arrays, wind turbines, short-term electrical storage (lithium-ion batteries), long-term hydrogen storage (compressed-gas tanks), and one or more electrolyzer technologies. Three commercial or near-commercial electrolysis routes dominate: alkaline (ALK), proton-exchange membrane (PEM), and solid-oxide (SOEC). ALK offers lower capital cost and mature manufacturing but exhibits limited dynamic response and reduced efficiency at partial load. PEM provides rapid response and wide operating windows, making it attractive for variable renewable input, albeit at higher capital cost linked to precious-metal catalysts. SOEC promises the highest conversion efficiencies through high-temperature operation and potential heat integration, yet remains at an earlier stage of commercial deployment [3,8,11].

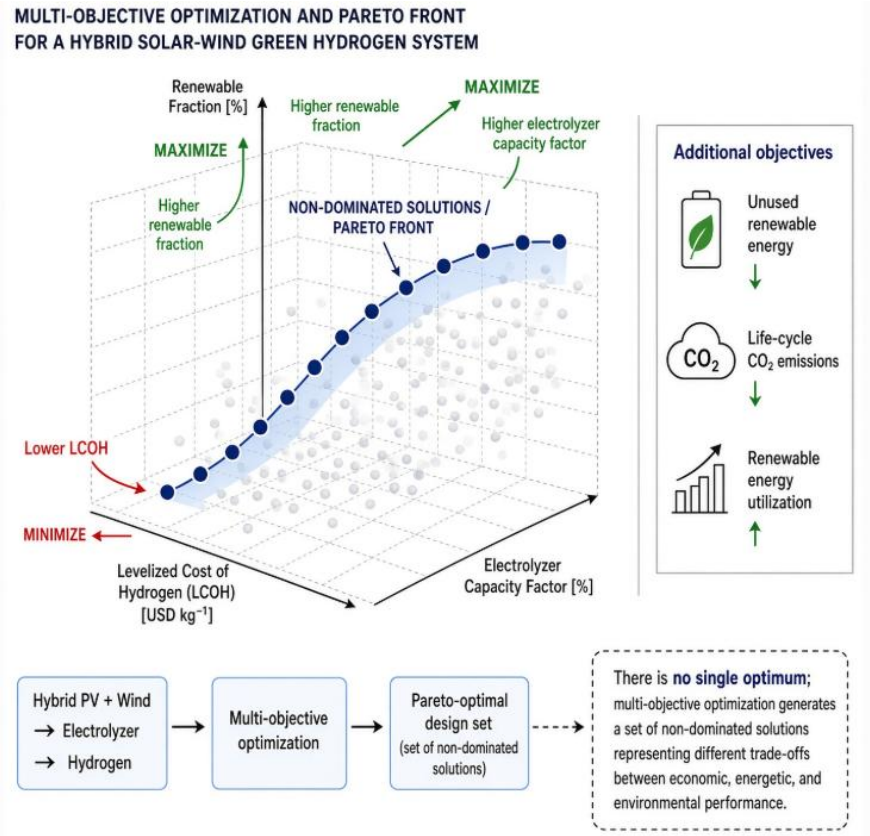
Figure 2 Green hydrogen production



4.2 Performance Metrics and Multi-Objective Formulation

The design problem is inherently multi-objective. Key indicators include LCOH, net present cost, renewable energy fraction, electrolyzer capacity factor, fraction of renewable energy that remains unused (curtailment), and life-cycle greenhouse-gas emissions. Studies employing NSGA-III on a 20,000-tonne-per-year solar–wind hydrogen system have demonstrated that careful capacity configuration can reduce unused energy to approximately 3.32 % while raising average electrolyzer load factor to 64.77 % [6]. Techno-economic assessments of large-scale electrolysis indicate that LCOH values in the range of 2–3.7 EUR kg^{-1} are attainable under favorable conditions, with further reductions projected toward 2 EUR kg^{-1} by mid-century [3]. Case studies in Kuwait and other high-resource locations report LCOH values between approximately 0.58 and 6.85 USD kg^{-1} depending on configuration and cost assumptions [4,12].

Figure 3 Multi-objective optimization and Pareto Front



4.3 Limitations of Current Practice

Many published studies still rely on static efficiency assumptions, coarse temporal resolution, or single-objective formulations. Such simplifications are equivalent to incomplete reconnaissance: they under-estimate the value of storage, mis-size the electrolyzer relative to renewable capacity, and provide limited insight into robustness under cost or resource uncertainty [8,9]. The literature increasingly recognizes the need for dynamic models, high-resolution meteorological data, and explicit multi-objective treatment, yet region-specific applications that integrate all of these elements remain scarce—particularly for Mexico.

V. Green Hydrogen Prospects in Mexico with Emphasis on Northern Sinaloa

Mexico's northern corridor (Sonora, Chihuahua, Coahuila, and Sinaloa) combines high solar irradiance with complementary wind resources. Spatial screening studies consistently identify these states among the national hotspots for low plant-gate LCOH and high production potential. Concrete project activity already exists in Sinaloa. The Tango Solar / DH2 development near El Fuerte contemplates approximately 921 MW of photovoltaic capacity coupled to electrolysis with a design output on the order of 40–41 kt H_2 per year. A parallel initiative, Pacífico Mexinol at Topolobampo, targets large-scale methanol production that incorporates green hydrogen. These projects illustrate both the commercial interest and the need for rigorous, region-specific techno-economic analysis.

Figure 4 Region of analysis

At the national level, the Mexican Hydrogen and Energy Transformation Association (H2México) has documented a pipeline of roughly two dozen to thirty initiatives representing more than US$21–22 billion in potential investment. Current production costs are commonly cited in the range of US$5–6 kg^{-1}, with industry projections indicating a trajectory toward approximately US$2 kg^{-1} under continued cost reduction and scale-up. A national renewable hydrogen plan is under preparation by the Ministry of Energy; until it is finalized, regulatory certainty remains a residual source of uncertainty for investors. Water availability, transmission capacity, and the still-maturing policy framework constitute the principal constraints. These factors reinforce the necessity of the information-gathering paradigm.

VI. Algorithmic Foundations: Bio-Inspired Multi-Objective Optimizers as Computational Reconnaissance Tools

The core of the "gathering-before-acting" paradigm is the set of computational tools that systematically explore the design space and quantify trade-offs before any irreversible capital commitment is made. Multi-objective evolutionary algorithms (MOEAs) are particularly well suited to this task because they maintain a population of candidate solutions that simultaneously sample different regions of the objective space—exactly the role played by scouts in biological systems.

6.1 Classical Multi-Objective Evolutionary Algorithms

6.1.1 NSGA-II

The Non-dominated Sorting Genetic Algorithm II (NSGA-II), proposed by Deb et al. [13], remains the most widely used MOEA in energy-system design. It employs a fast non-dominated sorting procedure of computational complexity $O(MN^2)$ (where M is the number of objectives and N the population size), an elitist selection mechanism that combines parent and offspring populations, and a crowding-distance metric that preserves diversity along the Pareto front. For two- and three-objective problems typical of hybrid hydrogen systems (e.g., LCOH versus renewable fraction versus capacity factor), NSGA-II has demonstrated reliable convergence and well-distributed fronts [6,9]. Its principal limitation appears when the number of objectives exceeds three, at which point the proportion of non-dominated solutions grows rapidly and crowding distance loses discriminatory power.

6.1.2 NSGA-III

NSGA-III [14] extends the NSGA-II framework to many-objective problems by replacing the crowding-distance operator with a set of predefined reference points distributed on a normalized hyperplane. Solutions are associated with the nearest reference point, and niche preservation is enforced by preferring under-represented reference directions. This mechanism maintains diversity even when four or more objectives are present. In the context of green-hydrogen design, NSGA-III has been successfully applied to capacity-configuration problems that simultaneously consider economic, environmental and energetic criteria, achieving, for example, unused-energy rates of 3.32 % and electrolyzer load factors of 64.77 % on a 20,000 t yr^{-1} system [6]. Because the typical objective vector for northern-Sinaloa studies comprises LCOH, renewable fraction, capacity factor, unused renewable energy and CO_2 emissions (five objectives), NSGA-III constitutes a natural baseline algorithm.

6.1.3 SPEA2

The Strength Pareto Evolutionary Algorithm 2 (SPEA2) [15] maintains an external archive of non-dominated solutions and assigns fitness on the basis of the number of solutions that dominate or are dominated by each individual (the "strength" concept). A nearest-neighbor density estimator further discriminates among solutions of equal strength, and a truncation procedure preserves boundary points when the archive exceeds its capacity. SPEA2 has shown excellent performance on problems whose Pareto fronts are discontinuous or concave—geometries that frequently arise when discrete technology choices (ALK versus PEM versus SOEC) or integer capacity constraints are present. Comparative studies on renewable-hydrogen systems indicate that SPEA2 and NSGA-II often yield complementary fronts, making parallel execution of both algorithms a useful diversity-enhancing strategy [9].

6.1.4 MOPSO

Multi-Objective Particle Swarm Optimization (MOPSO) [16] adapts the social and cognitive learning mechanisms of particle-swarm optimization to the multi-objective setting. Each particle maintains a personal best archive; a global repository of non-dominated solutions supplies the social attractor. A mutation operator is typically added to counteract premature convergence. Although MOPSO can converge faster than genetic algorithms on certain continuous problems, it may exhibit lower diversity on highly multi-modal landscapes. Hybridization of MOPSO velocity updates with non-dominated sorting (as in NSGA-II/III) has been shown to improve both convergence speed and front coverage for hybrid renewable sizing tasks.

6.2 Nature-Inspired Enhancements

6.2.1 Hippopotamus Optimization Algorithm

The Hippopotamus Optimization (HO) algorithm, introduced by Amiri et al. in 2024 [5], abstracts three characteristic behaviors of hippopotamus groups into a trinary-phase metaheuristic: (i) position updating inside resource-rich aquatic environments (exploration of promising basins), (ii) defensive responses against predators (intensification around high-quality solutions under pressure), and (iii) evasion maneuvers (escape from local optima). On a suite of 161 benchmark functions the algorithm ranked first on 115 instances, demonstrating a strong simultaneous capacity for exploration and exploitation. Subsequent applications to the optimal sizing of hybrid photovoltaic–wind–battery systems have confirmed competitive performance against classical particle-swarm and other swarm-based methods on cost–reliability objectives [17]. Because the algorithm's operators already encode resource assessment and adaptive response under threat, it maps naturally onto the reconnaissance metaphor advanced in this paper. Multi-objective extensions of HO (MOHO) can be constructed by embedding its position-update rules inside a non-dominated sorting or archive-based selection framework.

6.2.2 Sexual-Selection-Inspired Operators

Sexual-selection mechanisms introduce differential selection pressure, mate choice, and intra-sexual competition into the evolutionary population. High-quality individuals (those occupying sparsely populated regions of a high-quality Pareto front) are preferentially selected as mates, while competitive interactions among similar solutions intensify local search. These operators act as adaptive filters that concentrate computational effort around promising regions while still maintaining sufficient diversity to continue sampling alternative strategies—precisely the dual requirement of thorough reconnaissance followed by decisive action. When hybridized with the ranking machinery of NSGA-III or the archive of SPEA2, sexual-selection operators improve both the convergence rate and the uniformity of the final front on multi-objective energy-system problems.

6.3 Recommended Hybrid Algorithmic Framework for Northern Sinaloa

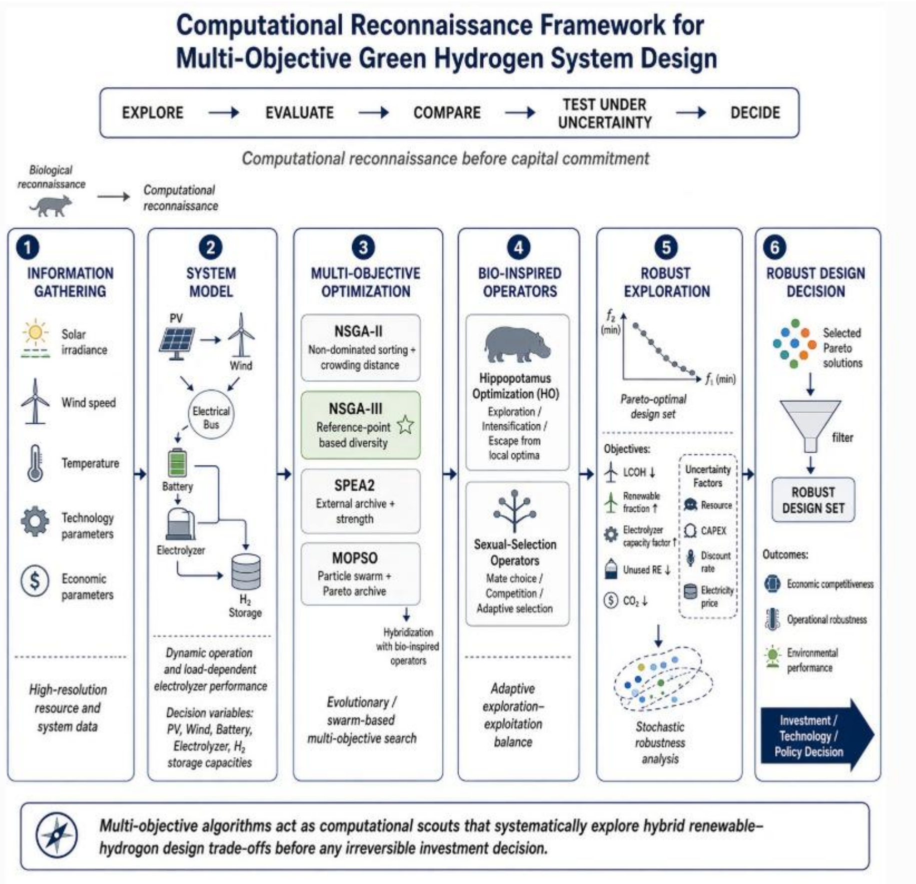
A practical configuration for the region would combine the following elements:

5. Decision variables: installed capacities of PV, wind, electrolyzer (ALK/PEM/SOEC), battery storage and hydrogen storage, together with key operational set-points (e.g., minimum electrolyzer load fraction, storage dispatch priorities).
6. Objective vector (five-dimensional): minimize LCOH; maximize renewable fraction; maximize electrolyzer capacity factor; minimize unused renewable energy; minimize life-cycle CO_2 emissions.
7. Core optimizer: NSGA-III (reference-point based) or SPEA2 (archive based), providing the non-dominated ranking and diversity preservation backbone.

8. Bio-inspired variation operators: HO position-update rules and/or sexual-selection mate-choice operators replace or augment classical crossover and mutation, thereby injecting adaptive scouting and intensified local search.
9. Uncertainty handling: at each generation a subset of promising solutions is re-evaluated under stochastic samples of resource series, capital costs and discount rates; the resulting distributional information is incorporated into the fitness assignment (e.g., via expected value, conditional value-at-risk, or information-gap criteria).

The resulting Pareto set constitutes the computational analogue of a comprehensive scout report. Decision makers can then select configurations that balance economic competitiveness with operational robustness under the specific meteorological and market conditions of northern Sinaloa.

Figure 5 Multi-objective Green Hydrogen System Design



VII. Integrated Research Agenda

Building on the preceding analysis, we propose the following research priorities:

10. Develop and openly share validated, high-resolution solar–wind data sets for northern Sinaloa and adjacent states, accompanied by quantitative complementarity metrics.
11. Advance dynamic, load-dependent models of ALK, PEM and SOEC electrolyzers suitable for annual hourly simulation and optimization [3,8].
12. Implement and benchmark hybrid bio-inspired multi-objective algorithms (NSGA-III / SPEA2 + HO / sexual-selection operators) on realistic northern-Sinaloa case studies that include both off-grid and grid-connected topologies.
13. Embed stochastic uncertainty analysis inside the evolutionary loop so that the Pareto front itself reflects robustness [10].
14. Translate the resulting quantitative guidelines into decision-support tools usable by project developers (including existing industry partners such as DH2) and into policy-relevant recommendations for the emerging national hydrogen strategy.

VIII. Conclusions

Green hydrogen systems in Mexico, and particularly in the high-resource northern corridor that includes Sinaloa, stand at a critical juncture. The technical and economic potential is substantial, yet the risks of premature commitment under incomplete information are equally real. By adopting the biological principle of gathering information before acting, researchers and practitioners can reorganize the design workflow around systematic reconnaissance: resource characterization, dynamic process modeling, multi-objective Pareto exploration, and uncertainty quantification.

Multi-objective evolutionary algorithms, especially when enriched by recent nature-inspired mechanisms such as the Hippopotamus Optimization Algorithm and sexual-selection operators, constitute the natural computational instruments for this reconnaissance. Applied to northern Sinaloa case studies, they can generate the quantitative evidence needed to reduce investment risk, inform technology choice, and support the formulation of a coherent national hydrogen strategy. In doing so, the community will move from acting on limited information to deciding on the basis of comprehensive, multi-objective, uncertainty-aware insight—exactly the strategy that evolution has favored in successful animal populations.

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