Optimizing Electrolyser Size for Green Hydrogen Production using Differential Evolution Algorithm

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1 Introduction

The Differential Evolution (DE) algorithm is a robust evolutionary optimization technique for solving complex, non-linear, and multi-dimensional problems. It excels at optimizing real-valued parameters by iteratively refining a population of candidate solutions. This report examines a real-world application of DE in optimizing the size and cost of electrolysers coupled with offshore wind farms (OWFs) for green hydrogen production, as detailed in a 2025 study by Dinh et al. [1] in the *International Journal of Hydrogen Energy*. The study uses DE to minimize the levelised cost of hydrogen ($LCOH_2$), supported by mathematical models for wind resources and OWF power output.

2 Use Case: Optimizing Electrolyser Size for Green Hydrogen Production

2.1 Background

Green hydrogen, produced via electrolysis using renewable sources like offshore wind, is a key solution for reducing CO_2 emissions. Electrolysers split water into hydrogen and oxygen using electricity, and when powered by renewables, the process is carbon-free. The study focuses on integrating electrolysers with OWFs, requiring precise sizing to minimize $LCOH_2$, the cost per kilogram of hydrogen over the project's lifetime. DE is used to determine the optimal electrolyser capacity for two setups: Offshore Electrolyser (Offshore-EL, electrolyser on an offshore platform) and Onshore Electrolyser (Onshore-EL, electrolyser onshore, powered via HVDC transmission).

2.2 Problem Statement

The objective is to minimize $LCOH_2$ by optimizing the electrolyser capacity relative to the OWF's power output. Key challenges include:

- Balancing electrolyser size, capital costs (e.g., equipment, infrastructure), and hydrogen production efficiency.
- Accounting for variable wind speeds that affect energy availability.
- Managing cost differences between offshore and onshore configurations, such as hydrogen pipelines versus HVDC cables.

2.3 Algorithm of Differential Evolution

DE iteratively optimizes the electrolyser capacity, expressed as a percentage of the OWF's 600 MW capacity. The algorithm follows these steps:

1. **Initialization**: A population of candidate electrolyser capacities is generated, each a real-valued ratio (e.g., 0.9 for 90% of OWF capacity).
2. **Mutation**: For each individual x_i in the population, a mutant vector is created:

   $$v_i = x_{r1} + F \cdot (x_{r2} - x_{r3})$$

   where x_{r1}, x_{r2}, x_{r3} are randomly chosen individuals, and F is the mutation factor (typically 0.5–1), controlling the step size.
3. **Crossover**: A trial vector is formed by combining the mutant vector v_i with the parent x_i, using a crossover probability CR (typically 0.8–1).

4. **Selection**: The trial vector's $LCOH_2$ is calculated, and the individual with the lower $LCOH_2$ is retained.

5. **Iteration**: The process repeats until $LCOH_2$ stabilizes, as shown in the study's convergence graphs (Fig. 8).

2.4 Mathematical Models

The DE algorithm operates within a techno-economic framework, using the following equations:

1. **Wind Speed Distribution (Weibull Function)**: Wind speed v is modeled using the Weibull probability density function to capture variability:

$$f_w(k, C) = \frac{k}{C}\left(\frac{v}{C}\right)^{k-1} e^{-\left(\frac{v}{C}\right)^k}$$

where:

- k: Shape parameter (dimensionless), affecting the distribution's shape.
- C: Scale parameter (m/s), related to average wind speed.
- v: Wind speed (m/s).
- e: Base of the natural logarithm (≈ 2.718).

This equation determines the likelihood of different wind speeds, influencing OWF energy output.

2. **OWF Power Output**: The power output of the OWF at wind speed v is calculated using a piecewise function:

$$P_{\mathrm{OWF,w}}(v) = \begin{cases} 0, & \text{if } v < v_{\mathrm{ci}} \text{ or } v \geq v_{\mathrm{co}} \\ 0.5 \cdot \rho \cdot c_p \cdot A_{\mathrm{swept}} \cdot v^3 \cdot N_{\mathrm{wt}}, & \text{if } v_{\mathrm{ci}} \leq v < v_r \\ P_r \cdot N_{\mathrm{wt}}, & \text{if } v_r \leq v < v_{\mathrm{co}} \end{cases}$$

where:

- ρ: Air density (kg/m^3).
- c_p: Power coefficient of the turbine (dimensionless, typically 0.4–0.5).
- A_{swept}: Swept area of the turbine rotor (m^2).
- v: Wind speed (m/s).
- N_{wt}: Number of turbines (40 in the case study).
- P_r: Rated power per turbine (15 MW).
- v_{ci}: Cut-in wind speed (m/s).
- v_{co}: Cut-out wind speed (m/s).
- v_r: Rated wind speed (m/s).

This equation calculates the energy available for electrolysis, critical for hydrogen production.

3. **Levelised Cost of Hydrogen ($\mathbf{LCOH_2}$)**: The objective function, $LCOH_2$, is:

$$\mathrm{LCOH_2} = \frac{\text{Total Discounted Costs}}{\text{Total Hydrogen Production}}$$

where:

- Total Discounted Costs: Sum of capital costs (electrolyser, turbines, foundations, pipelines/HVDC) and operational costs, discounted at 8% over the project lifetime (€).
- Total Hydrogen Production: Annual hydrogen output (kg), based on electrolyser capacity, efficiency, and OWF power output.

DE minimizes LCOH_2 by adjusting the electrolyser capacity.

4. **Water Consumption for Electrolysis**: Water needed for hydrogen production is:

$$V_{\text{H}_2} = V_{\text{H}_2\text{O}} \cdot \frac{P_{\text{EL,rated}} \cdot \eta}{\text{LHV}_{\text{H}_2}}$$

where:

- $V_{\text{H}_2\text{O}}$: Water consumption per kg of hydrogen (0.015 m^3/kg).
- $P_{\text{EL,rated}}$: Rated power of the electrolyser (MW).
- η: Stack efficiency of the electrolyser (dimensionless, typically 0.6–0.8).
- LHV_{H_2}: Lower heating value of hydrogen (33.3 kWh/kg).

This ensures water requirements are included in the cost model.

2.5 Population Features in DE

The population consists of candidate electrolyser capacities with these features:

1. **Electrolyser Capacity Ratio**:
   - Each individual is a real-valued ratio of electrolyser capacity to OWF capacity (e.g., 0.9141 for 548.46 MW).
   - Range: 0% to 100%, with optimal ratios of 91.41% (Offshore-EL) and 94.54% (Onshore-EL).
2. **Population Size**:
   - Typically 10–100 individuals (not specified in the study), balancing exploration and computational efficiency.
3. **Fitness Evaluation**:
   - Fitness is LCOH_2, calculated using the techno-economic model and the above equations.
4. **Diversity and Evolution**:
   - Mutation and crossover generate new capacities, ensuring diverse exploration.
   - The population evolves over iterations, converging to optimal capacities (Fig. 8).

3 Case Study Details

The study optimizes a 600 MW OWF near Cork, Ireland (51°38'24.0"N, 7°42'36.0"W), with 40 turbines (15 MW each) in a 4×10 layout. Proton Exchange Membrane (PEM) electrolysers are used for their fast response to variable wind energy. Costs are projected for 2030, with an 8% discount rate. DE optimizes capacities for Offshore-EL and Onshore-EL configurations.

4 Results

DE yielded:

- **Optimal Electrolyser Capacity**:
  - Offshore-EL: 91.41% (548.46 MW), $LCOH_2$ = €3.7901/kg, hydrogen production = 57.55 kt/year.
  - Onshore-EL: 94.54% (567.24 MW), $LCOH_2$ = €4.292/kg, hydrogen production = 55.5 kt/year.
- **Cost Comparison** (Table 4):
  - Offshore-EL had lower $LCOH_2$ than Onshore-EL due to reduced transmission losses, despite higher capital costs (€1764M vs. €1974M).
  - Non-optimal ratios (e.g., 60%, 100%) increased $LCOH_2$, showing DE's precision.
- **Sensitivity Analysis** (Table 5):
  - Discount rate was most influential (±1% change → 0.65% $LCOH_2$ change).
  - Turbine costs (±1% → 0.37–0.41% $LCOH_2$ change) and wind resources also mattered.
- **Spatial Insights**:
  - $LCOH_2$ maps for Ireland's offshore areas, based on wind, depth, and port proximity, aid project planning.

5 Impact and Significance

DE's application shows its power in complex energy optimization. By minimizing $LCOH_2$, it enhances green hydrogen's viability. Implications include:

- **Policy**: Low-interest loans can reduce discount rates, lowering $LCOH_2$.
- **Site Selection**: Strong wind resources cut costs.
- **Technology**: PEM electrolysers suit offshore variability.

6 Comparison with Other Methods

DE surpasses gradient-based methods because:

- It handles non-linear, non-differentiable functions like $LCOH_2$.
- It avoids local optima via population diversity.
- It's efficient for multi-parameter problems.

7 Conclusion

The DE application in optimizing electrolyser size for green hydrogen, as shown by Dinh et al. [1] (2025), is a strong real-world case. Supported by clear equations like the Weibull distribution and OWF power output, DE minimizes $LCOH_2$, finding optimal capacities (91.41% for Offshore-EL, 94.54% for Onshore-EL). This highlights DE's role in renewable energy optimization, offering a blueprint for AI-driven sustainable energy solutions.

References

[1] Dinh, et al. (2025). Optimizing Electrolyser Size for Green Hydrogen Production Using Differential Evolution. *International Journal of Hydrogen Energy*. .