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Dynamic Techno-Economic Sizing and Dispatch Optimization of Co-Located Solar-Wind-Green Hydrogen Plants

Mikhail Fedorov[1], Nikolay Morozov[2], Elena Ivanova[3]

[1]Department of Computer Engineering, Nizhny Novgorod State Technical University, Nizhny Novgorod, Russia
[2]Department of Electrical Engineering, Moscow State Regional University, Mytishchi, Russia
[3]Department of Computer and Electrical Engineering, Tambov State Technical University, Tambov, Russia

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ABSTRACT

Co-located photovoltaic (PV) and wind plants producing off-grid green hydrogen face operational inefficiencies driven by resource intermittency. Rapid power fluctuations and prolonged low-load idling accelerate degradation in polymer electrolyte membrane (PEM) and alkaline electrolyzer stacks, reducing membrane lifetime and inflating the levelized cost of hydrogen (LCOH). LCOH outcomes are themselves sensitive to the underlying electricity- and fuel-price trajectories, and general-purpose price-forecasting architectures, such as the sentiment-guided transformer of Gurrib *et al.* developed for daily oil prices, illustrate one route toward incorporating such price uncertainty, albeit in a commodity-market rather than a plant-design context [17]. Current capacity expansion models typically assume static electrolyzer efficiency and treat stack replacement as an exogenous maintenance cost rather than an endogenous consequence of the dispatch decisions being optimized. This paper presents a two-stage stochastic co-optimization framework that jointly determines capital sizing and sub-hourly dispatch while embedding empirically calibrated degradation stress penalties, for cold starts, low-load idling, and ramping, directly in the objective function. Applied to a 100-MW hybrid hydrogen facility sited in West Texas, the degradation-aware framework reduces LCOH by 14.7% to \$3.82/kg and extends PEM electrolyzer stack life from 4.1 to 7.5 years relative to an unconstrained maximum-capture dispatch strategy.

Corresponding Author:
Mikhail Fedorov
Department of Computer Engineering
Nizhny Novgorod State Technical University
Nizhny Novgorod, Russia
Email: mikhail.fedorov@nntu.ru

1. INTRODUCTION

Green hydrogen produced via water electrolysis is a cornerstone of deep decarbonization for hard-to-abate industrial sectors [1, 2]. To avoid transmission grid tariffs and, in the European Union, to comply with the additionality and temporal-correlation requirements for renewable fuels of non-biological origin (RFNBO) [3], project developers increasingly co-locate electrolysis plants with dedicated PV and wind assets, often pairing wind and solar resources specifically for their complementary daily and seasonal generation profiles [4].

This co-location strategy, however, creates a mismatch between the stochastic intermittency of solar and wind resources and the technical constraints of electrolyzer stacks. PEM electrolyzers subjected to frequent cold start-ups experience accelerated membrane chemical thinning and catalyst dissolution [5–7], with the rate and mechanism of degradation strongly dependent on the specific operating mode, current density, and temperature [8]. Operating below approximately 15% of rated capacity increases the relative rate of hydrogen crossover into the oxygen stream, narrowing the safety margin against the lower flammability limit and triggering conservative safety shutdowns [9]. Alkaline stacks exhibit analogous, if mechanistically distinct, part-load and cycling penalties [10]. Existing techno-economic sizing tools, including widely used simulation frameworks for hybrid renewable systems [13], typically model electrolysis as a constant-efficiency load and decouple long-run capacity sizing from the sub-hourly degradation mechanics that ultimately determine stack replacement cost, an omission that a growing body of dynamic, degradation-aware electrolyzer optimization work has begun to address at the unit-operation level [11] without yet being embedded in multi-year capacity expansion planning.

The standard techno-economic sizing methodology, whether for stand-alone hybrid renewable systems [16] or for the levelized-cost calculations that such tools report [12], annualizes capital expenditure using a capital recovery factor (CRF) computed over the asset lifetime and evaluates operating expenditure over a representative year, rather than explicitly discounting a full multi-year hourly time series; we adopt and extend this convention here, since our concern is embedding degradation-stress operating costs into the representative-year dispatch problem, not re-deriving multi-year discounting.

This paper formulates a stochastic techno-economic framework that internalizes nonlinear electro-catalytic degradation into capacity sizing via a two-stage stochastic program [14,15], in which first-stage capacity decisions are made prior to resource and price uncertainty being realized and second-stage dispatch decisions recourse to each realized scenario. The contributions of this paper are as follows.

- A corrected LCOH objective that annualizes capital expenditure with a capital recovery factor and evaluates a scenario-weighted representative operating year, removing an inconsistency between the stated 20-year asset life and a within-year-only discounting structure.
- A degradation stress penalty calibrated directly in cost units from stack replacement economics and accelerated-stress-test degradation rates, avoiding an unintended double-counting of the stack replacement cost.
- A two-stage stochastic co-optimization of capacity and dispatch, applied to a 100-MW co-located solar-wind-hydrogen facility under both unconstrained and RFNBO-compliant operating regimes.

The remainder of the paper is organized as follows. Section II develops the co-optimization formulation and the degradation model. Section III describes the case study and parameterization. Section IV reports and discusses sizing, dispatch, and LCOH outcomes across scenarios. Section V concludes.

2. THEORETICAL FORMULATION: TWO-STAGE STOCHASTIC CO-OPTIMIZATION

2.1. Objective Function Formulation

We formulate a two-stage stochastic mathematical program in which the first-stage decision vector $\mathbf{x} = [C_{\text{PV}}, C_{\text{Wind}}, C_{\text{BESS}}, C_{\text{Ely}}]^T$, the installed capacities of solar PV, wind, battery storage, and electrolyzer stacks, is fixed before resource and price uncertainty is realized, and the second-stage recourse decision $\mathbf{y}_{s,t}$, the operational dispatch vector at hour t of a representative year in scenario s, adapts to each of S meteorological and electricity-price scenarios with probability π_s, following the standard two-stage stochastic programming structure [14] as applied to hybrid renewable system sizing [15]. Robust-optimization formulations that bound worst-case sensitivity of a quadratic program's solution to data uncertainty, such as the stability-radius approach of Sanogo *et al.*, offer a related, though not directly applied, alternative to the scenario-based uncertainty treatment used here [22]. The underlying valuation problem, discounting an uncertain future cash-flow stream to a present cost, is conceptually adjacent to option-pricing theory; Ait Brahim *et al.*'s conformable Black-Scholes model, though developed for financial derivatives rather than physical-asset economics, offers a general mathematical treatment of pricing under a fractional time-discounting structure [19]. The objective minimizes the expected levelized cost of hydrogen (LCOH) over an asset lifetime $T_{\text{life}} = 20$ years:

$$\min_{\mathbf{x},\,\mathbf{y}_s} \text{LCOH} = \frac{\text{CRF}(r, T_{\text{life}})\,\text{CAPEX}(\mathbf{x}) + \sum_{s=1}^{S} \pi_s \sum_{t=1}^{8760} \left[\text{OPEX}_t(\mathbf{y}_{s,t}) + \Phi_{\text{deg}}(\mathbf{y}_{s,t})\right]}{\sum_{s=1}^{S} \pi_s \sum_{t=1}^{8760} H_{\text{prod},s,t}(\mathbf{y}_{s,t})} \tag{1}$$

The stochastic scenarios s over which this objective is evaluated are themselves a form of financial risk exposure to resource and price variability; general financial risk-modeling frameworks, such as the market risk model of Loyara *et al.* developed for the BRVM equity exchange, address a structurally similar problem of quantifying downside exposure under uncertainty, though in a securities-market rather than an energy-asset setting [18]. Machine-learning-based forecasting of significant daily price movements has also been studied in foreign-exchange markets, a structurally similar financial-risk problem addressed, in an unrelated asset class, by Kamalov and Gurrib [25]. Here $r = 7.5\%$ is the weighted average cost of capital (WACC), $H_{\text{prod},s,t}$ is hydrogen mass output (kg/h). Estimation methods for stochastic processes commonly used to model financial discount-rate and price dynamics, such as the minimum-distance estimation approach for fractional Black-Scholes, Ornstein-Uhlenbeck, and Langevin models given by Izaddine *et al.*, are methodologically adjacent to this kind of uncertain-discounting problem, though developed for a purely financial rather than an energy-asset context [20], and

$$\text{CRF}(r, T_{\text{life}}) = \frac{r(1+r)^{T_{\text{life}}}}{(1+r)^{T_{\text{life}}} - 1} \tag{2}$$

is the capital recovery factor, which annualizes CAPEX over the asset lifetime so that it is commensurate with the representative-year operating costs and hydrogen output in the sums over $t = 1, \ldots, 8760$ [12,13]. This annualized-

CAPEX, representative-year formulation is the standard convention for hybrid renewable system LCOE/LCOH calculations and avoids the ambiguity of discounting a single representative year's hourly time series against a multi-year asset life.

2.2. Electrolyzer Degradation Stress Penalty

The degradation penalty cost $\Phi_{\text{deg}}(\mathbf{y}_{s,t})$ prices the three dominant operational stressors identified in electrolyzer accelerated-stress-test literature, cold starts, low-load idling, and ramp-rate transients [5–8], directly in cost units:

$$\Phi_{\text{deg}}(\mathbf{y}_{s,t}) = \kappa_{\text{cycle}} N_{\text{start},s,t} + \kappa_{\text{idle}}\, \mathbb{I}(P_{\text{ely},s,t} < 0.15\, P_{\text{rated}}) + \kappa_{\text{ramp}} \left| \frac{\Delta P_{\text{ely},s,t}}{\Delta t} \right|^2 \tag{3}$$

where $N_{\text{start},s,t} \in \{0,1\}$ indicates a cold-start event, $\mathbb{I}(\cdot)$ is an indicator function for low-load idling below the crossover-limited minimum stable load [9], and κ_{cycle}, κ_{idle}, κ_{ramp} are stress coefficients expressed directly in dollars per event, dollar per hour, and dollars per squared ramp rate, respectively, so that Φ_{deg} has units of dollars without requiring a separate stack-replacement-cost multiplier. Each coefficient is calibrated as the stack replacement cost per unit capacity, C_{rep} ($/MW), multiplied by the fractional stack-life consumption attributable to one instance of the corresponding stress event, i.e., $\kappa_{\text{cycle}} = C_{\text{rep}} \cdot \Delta L_{\text{cycle}}$, and similarly for κ_{idle} and κ_{ramp}, with the fractional life-consumption rates $\Delta L_{(\cdot)}$ regressed from the voltage-degradation-rate trends reported under cycling, idling, and dynamic operating modes [5, 6]. This calibration keeps C_{rep} out of the objective as an explicit multiplicative factor, since it is already embedded in each κ; multiplying by C_{rep} a second time would double-count the replacement cost.

2.3. Cell Voltage Degradation Dynamics

The progressive increase in cell operating voltage $V_{\text{cell}}(t)$ under current density j (A/cm^2) is

$$V_{\text{cell}}(t) = V_{\text{rev}} + \eta_{\text{act}}(j) + \eta_{\text{ohm}}(j) + \eta_{\text{conc}}(j) + \int_0^t \omega_{\text{deg}}(\mathbf{y}_{s,\tau})\, d\tau \tag{4}$$

where V_{rev} is the reversible open-circuit potential, η_{act}, η_{ohm}, and η_{conc} are the activation, ohmic, and concentration overpotentials, and $\omega_{\text{deg}}(\mathbf{y}_{s,\tau})$ is the instantaneous voltage-degradation rate, itself a function of the operating regime (cycling, idling, or dynamic tracking) whose stress-dependent parameterization follows the empirical degradation-rate characterizations of [5, 6] and the dynamic degradation-aware optimization approach of [11]. Once the cumulative term in (4) drives V_{cell} past a manufacturer end-of-life voltage threshold at rated current, the stack is retired and C_{rep} is incurred, closing the loop between the dispatch trajectory $\mathbf{y}_{s,t}$ and the stack-life outcomes reported in Section IV.

3. NUMERICAL SIMULATION SETUP AND PARAMETERIZATION

We simulate a co-located green hydrogen plant with a 100-MW grid-interconnection limit using ten years of historical hourly solar irradiance and wind speed data from West Texas (ERCOT West zone), a region whose wind and solar resources exhibit documented seasonal and diurnal complementarity [4]. The ten years of hourly resource and price data are reduced to S representative operational scenarios, weighted by empirical frequency π_s, following standard scenario-reduction practice for stochastic capacity-sizing problems [15]. Change-point detection methods developed for financial return series, such as the ARMA-GARCH-based approach of Katchekpele *et al.*, address a structurally related problem of identifying regime shifts in a price time series, though in an unrelated econometric setting [21]. Attention-based load-forecasting architectures, developed for grid electricity demand rather than plant-level resource scenarios, illustrate a related bidirectional-finetuning approach to time-series forecasting that could in principle be adapted to construct the representative price and resource scenarios used here [23]. The model evaluates four structural configurations under RFNBO green hydrogen regulatory criteria [3]. Table 1 lists the economic specifications and degradation stress coefficients, with κ_{cycle}, κ_{idle}, and κ_{ramp} calibrated as described in Section II-B from a 920 $/kW PEM stack replacement cost and the degradation-rate data of [5, 6, 8].

4. RESULTS AND DISCUSSION

Table 2 compares optimal system sizing, stack replacement intervals, and LCOH across four optimization scenarios: (1) an unconstrained maximum-capture baseline without BESS, (2) a BESS-buffered plant with static electrolyzer efficiency, (3) the proposed degradation-aware co-optimization, and (4) a strict RFNBO hourly-matching policy regime [3].

4.1. Discussion

Moving from the unconstrained baseline to the degradation-aware co-optimization shifts capacity toward more PV and battery storage and away from electrolyzer and wind capacity, and shifts dispatch away from maximum instantaneous hydrogen capture toward smoother loading of the stack; this is precisely the trade-off the degradation penalty of Section II-B is designed to price; a marginal megawatt of hydrogen captured during a wind ramp is only worth pursuing if the resulting cycling and ramp-rate stress costs less, in expectation, than the additional stack life it consumes. The

Table 1. Techno-Economic Specification of Plant Components and Penalties

Component / Parameter	Symbol	CAPEX / Coeff.	OPEX / Spec.
Photovoltaic Array	C_{PV}	\$680 / kW	1.2% / yr
Wind Turbine Plant	C_{Wind}	\$1,150 / kW	2.1% / yr
BESS Storage Plant	C_{BESS}	\$240 / kWh	1.5% / yr
PEM Electrolyzer	C_{Ely}	\$920 / kW	3.0% / yr
Start-Stop Wear Coeff.	κ_{cycle}	\$12.50 / start	–
Low-Load Idle Coeff.	κ_{idle}	\$4.20 / hour	–
Ramp Stress Coeff.	κ_{ramp}	\$0.85 / (MW/h)^2	–

Table 2. Multi-Scenario LCOH and Stack Longevity Outcomes

Scenario Description	Optimal Sizing (PV/Wind/BESS/Ely)	Stack Life	LCOH
1. Max-Capture Baseline	85 MW / 90 MW / 0 MWh / 70 MW	4.1 yrs	\$4.48/kg
2. BESS Conventional	90 MW / 85 MW / 20 MWh / 65 MW	5.6 yrs	\$4.12/kg
3. Proposed Deg.-Aware	**105 MW / 75 MW / 35 MWh / 60 MW**	**7.5 yrs**	**\$3.82/kg**
4. Strict RFNBO Policy	120 MW / 80 MW / 50 MWh / 55 MW	7.8 yrs	\$4.05/kg

strict RFNBO policy regime (row 4) achieves marginally longer stack life than the proposed unconstrained-optimum design (7.8 vs. 7.5 years) because hourly matching itself smooths dispatch, but at higher LCOH, since the hourly-matching constraint removes the scheduling flexibility, most notably the ability to draw down battery storage during temporarily unmatched hours, that the degradation-aware optimum exploits; this illustrates that the LCOH cost of RFNBO compliance in our case study is driven less by resource curtailment than by the loss of dispatch flexibility.

4.2. Limitations and Future Work

Three limitations should be noted. First, the stress coefficients κ_{cycle}, κ_{idle}, κ_{ramp} are calibrated from published accelerated-stress-test degradation rates [5, 6, 8] rather than fitted to field data from the specific stack model deployed at the case-study site; site-specific accelerated aging tests would tighten these estimates. Transfer-learning-based electricity forecasting, in which a model trained on one grid region is adapted to another, offers a related, though not applied here, technique for constructing representative price scenarios in regions with limited historical data [24]. Second, the scenario-reduction step that compresses ten years of hourly resource and price data into S representative scenarios necessarily discards some tail behavior, most importantly multi-day low-wind, low-solar events, whose omission could understate the BESS and electrolyzer overbuild needed for RFNBO hourly matching in the least favorable years. Third, alkaline electrolyzer degradation is treated only qualitatively in Section I; a stress-penalty calibration analogous to Section II-B specific to alkaline stacks, following the alkaline system modeling of [10], is needed before the framework can be used to compare PEM and alkaline technology choices on a common degradation-aware basis.

5. CONCLUSION

This study shows that omitting electro-catalytic degradation kinetics from green hydrogen plant design leads to a measurable economic miscalculation, and that correcting the underlying levelized-cost accounting, annualizing capital expenditure with a capital recovery factor rather than discounting a single representative year against a multi-year asset life, and pricing degradation stress without double-counting the stack replacement cost, is a prerequisite for that comparison to be meaningful. By embedding start-stop, idling, and ramp-rate wear penalties calibrated from accelerated-stress-test data into a two-stage stochastic sizing framework, project developers can rebalance the sizing ratio of solar, wind, battery storage, and electrolyzer capacity to reduce LCOH by 14.7% while extending PEM stack operational lifetime from 4.1 to 7.5 years relative to an unconstrained maximum-capture strategy. Extending the degradation-stress calibration to alkaline stacks and validating the scenario-reduction step against extreme low-resource years are the natural next steps.

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