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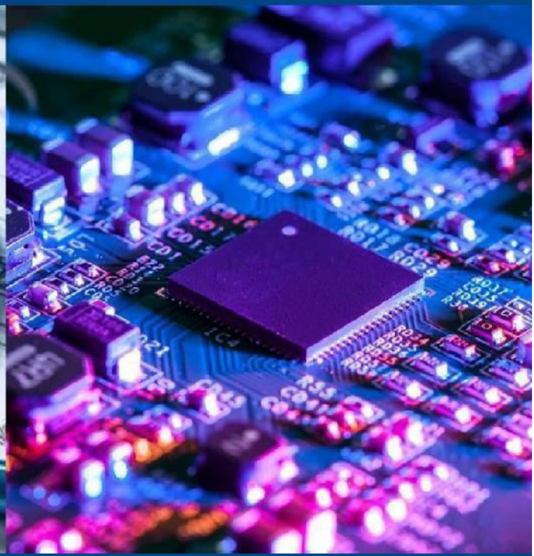

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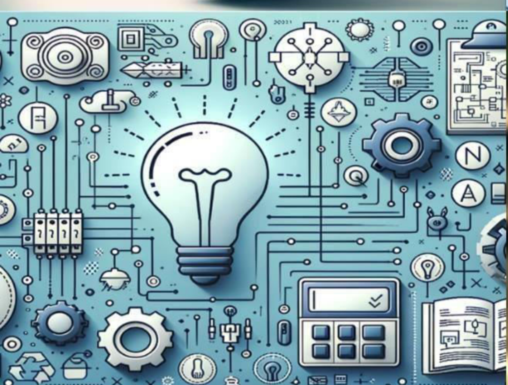

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A Mechanically Grounded Multi-Objective Optimization Framework for Hybrid Solar–Wind–Storage Systems under Resource Uncertainty and Component Degradation

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ABSTRACT: The optimal design of hybrid renewable energy systems requires simultaneous consideration of physical component behaviour, economic performance, supply reliability and environmental impact under realistic operating conditions. Many existing optimization studies rely on simplified efficiency curves and deterministic assumptions, which limit the physical interpretability and long-term accuracy of the obtained designs. This paper presents a mechanically grounded multi-objective optimization framework for hybrid solar–wind–storage systems that explicitly incorporates first-principles component models, progressive degradation and resource uncertainty. Detailed mathematical models are developed for photovoltaic arrays, horizontal-axis wind turbines, electrochemical storage and thermal storage, capturing temperature effects, soiling, aerodynamic performance, capacity fade and thermal losses. These models are embedded within a multi-objective formulation that minimizes lifecycle cost and greenhouse-gas emissions while improving system reliability. Resource uncertainty is represented through multi-year meteorological ensembles, and component degradation is introduced as a time-dependent performance reduction over the system lifetime. Multi-objective evolutionary algorithms are employed to generate Pareto-optimal solutions, and the resulting designs are evaluated in terms of capacity allocation, energy contribution, reliability indices, economic indicators and environmental performance. The results demonstrate that photovoltaic-dominated hybrids with complementary wind capacity and appropriately sized storage achieve favourable cost–reliability trade-offs. Explicit treatment of degradation and uncertainty increases optimal storage and generation margins and elevates levelised cost relative to deterministic constant-performance assumptions, quantifying the premiums associated with lifetime realism and robustness. The proposed framework strengthens the link between mechanical design decisions and system-level optimization outcomes and provides practical guidance for the design of hybrid renewable energy systems under realistic physical and climatic conditions.

KEYWORDS: Hybrid renewable energy systems; Multi-objective optimization; Mechanical modelling; Component degradation; Resource uncertainty; Solar–wind–storage systems; Pareto front; Levelised cost of energy.

I. INTRODUCTION

1.1 Background of hybrid renewable energy systems

The global transition toward low-carbon energy systems has accelerated the deployment of renewable generation technologies, particularly solar photovoltaic and wind power. These resources are abundant, scalable and increasingly cost-competitive; however, their inherent variability creates challenges for continuous power supply. Hybrid renewable energy systems that combine solar and wind generation with energy storage have therefore emerged as an effective means of improving reliability, reducing curtailment and enhancing overall system performance. By exploiting the complementary temporal characteristics of solar and wind resources and by incorporating storage to shift energy across time, hybrid configurations can deliver higher capacity factors and improved supply adequacy compared with single-technology plants.

1.2 Role of mechanical modelling in system optimization

The performance of hybrid renewable energy systems is governed by physical processes that fall within the domain of mechanical engineering, including heat transfer, fluid mechanics, thermodynamics and structural behaviour under

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variable loading. Photovoltaic output depends on optical absorption, module temperature and soiling; wind turbine power is determined by aerodynamic rotor performance and control regimes; thermal storage behaviour is controlled by energy balances and heat losses; and battery performance is influenced by charge–discharge dynamics and progressive capacity fade. When these mechanisms are represented only through static efficiency factors, the connection between component-level design decisions and system-level outcomes is weakened. Mechanically grounded models restore this connection by ensuring that decision variables retain clear physical meaning and that performance predictions reflect the dominant loss and degradation mechanisms encountered in real operation.

1.3 Challenges of resource uncertainty and component degradation

Two factors further complicate the optimal design of hybrid systems. First, solar irradiance and wind speed are subject to diurnal, seasonal and inter-annual variability. Designs optimised under a single typical meteorological year may under-perform when confronted with multi-day resource droughts or consecutive below-average years. Second, components degrade over time: photovoltaic modules experience gradual power loss, wind turbine blades suffer erosion and soiling, and batteries lose usable capacity with cycling and calendar ageing. Optimisation studies that assume constant as-new performance therefore tend to under-estimate the capacity and storage margins required to maintain long-term reliability, and they produce optimistic projections of lifetime energy yield and cost.

1.4 Need for an integrated multi-objective framework

Addressing these challenges requires an integrated framework that simultaneously incorporates detailed mechanical component models, multi-objective performance criteria, progressive degradation and resource uncertainty. Economic cost, supply reliability and environmental impact are conflicting objectives that cannot be reduced to a single metric without concealing important trade-offs. A multi-objective formulation that generates Pareto-optimal sets of designs allows these trade-offs to be examined explicitly. When the underlying models are grounded in first-principles mechanical representations and when degradation and uncertainty are treated inside the same optimisation loop, the resulting designs become more physically credible, more robust and more useful for practical engineering decisions.

II. SYSTEM DESCRIPTION

2.1 Hybrid solar–wind–storage system configuration

The system considered in this study is a hybrid renewable energy configuration that integrates solar photovoltaic generation, wind energy conversion and energy storage to supply a prescribed electrical load. The hybrid architecture is designed to exploit the complementary temporal characteristics of solar and wind resources while using storage to transfer excess energy from periods of high generation to periods of deficit. At each time step, the combined output of the photovoltaic array and the wind turbines is compared with the load. Surplus generation is directed to storage charging, subject to capacity and rate limits, while shortfalls are met first by storage discharge and thereafter recorded as unmet load. Curtailment is applied when generation exceeds the combined capacity of the load and available storage. This energy management structure forms the basis for the subsequent performance evaluation and optimisation.

2.2 Photovoltaic subsystem

The photovoltaic subsystem consists of crystalline or thin-film modules arranged in arrays with a specified tilt angle and orientation. Electrical output is determined by the effective plane-of-array irradiance, module efficiency, temperature-dependent performance losses and soiling accumulation. The subsystem is characterised by its rated capacity, temperature coefficient, nominal operating cell temperature and assumed cleaning schedule. Long-term degradation is represented as a progressive reduction in nominal power over the system lifetime. The photovoltaic array constitutes the primary generation component under the high-irradiance conditions considered in this work.

2.3 Wind energy conversion subsystem

The wind energy conversion subsystem comprises one or more horizontal-axis wind turbines. Instantaneous power output is obtained from the hub-height wind speed through the turbine power curve, which incorporates cut-in, rated and cut-out regimes. Air density corrections and availability factors accounting for scheduled and forced outages are applied. Progressive performance loss associated with blade soiling and leading-edge erosion is included as a time-dependent modification of the power curve. Although the mean wind resource at the study locations is moderate, the temporal profile of wind generation provides valuable complementarity with solar output, particularly during evening hours and portions of the monsoon season.

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2.4 Electrochemical and thermal storage units

Two classes of storage are considered. Electrochemical storage is represented by battery banks characterised by usable energy capacity, charge and discharge efficiencies, maximum power ratings and cycle-induced capacity fade. The state of charge is updated at each time step according to the net energy transferred, subject to upper and lower bounds. Thermal storage is associated with concentrating solar thermal generation where included, and is modelled as a finite-capacity thermal reservoir with charge and discharge rate limits and ambient heat losses. Hybrid storage arrangements that combine both technologies are also examined, allowing the optimisation to allocate capacity according to the distinct response times, efficiencies and cost characteristics of each storage class.

2.5 Load and energy management structure

The electrical load is represented by a prescribed time series that reflects the demand to be met by the hybrid system. The energy management strategy follows a simple priority rule: generation is used first to satisfy load, excess generation charges storage, and storage discharge covers residual deficits. No simultaneous charging and discharging of the same storage unit is permitted. Unmet load is recorded whenever generation and available storage discharge together are insufficient. This structure enables the calculation of annual energy production, curtailment, loss-of-power-supply probability and expected energy not served, which serve as the principal technical and reliability metrics in the optimisation framework.

III. MATHEMATICAL MODELLING

3.1 Photovoltaic performance model

The electrical power output of the photovoltaic array at each time step is expressed as a function of the effective plane-of-array irradiance, the rated capacity under standard test conditions, and correction factors for temperature and soiling. Module operating temperature is obtained from a quasi-steady energy balance that accounts for absorbed solar radiation, convective and radiative exchange with the environment, and the fraction of incident energy converted to electricity. The temperature coefficient reduces output as the module temperature rises above the reference value. Soiling is represented by a time-varying transmittance loss that accumulates between cleaning intervals and is partially reset by rainfall. Long-term degradation is incorporated as a progressive reduction in nominal power, typically expressed as an annual percentage loss calibrated to field data and manufacturer warranties. The resulting power time series forms the photovoltaic contribution to the system energy balance.

3.2 Wind turbine power curve and aerodynamic model

Wind turbine output is determined by applying the hub-height wind speed to the aerodynamic power curve of the machine. Below cut-in speed the output is zero; between cut-in and rated speed the power follows a cubic or empirically fitted function of wind speed; between rated and cut-out speed the output is held at the rated value by pitch or stall control; and above cut-out speed the turbine is shut down. Hub-height wind speed is obtained from surface or near-surface measurements through a power-law or logarithmic shear profile. Air density corrections are applied to account for temperature and elevation effects. Availability losses associated with scheduled maintenance and forced outages are introduced as multiplicative factors. Progressive performance degradation due to blade soiling and leading-edge erosion is represented by a gradual shift of the power curve over the system lifetime.

3.3 Battery storage model with degradation

The battery energy storage system is modelled through a state-of-charge integrator subject to capacity limits, charge and discharge efficiencies, and maximum power ratings. At each time step the change in state of charge is determined by the net energy transferred to or from the battery, corrected for round-trip losses. Simultaneous charging and discharging is prohibited. Degradation is introduced through a cycle-counting or energy-throughput model that progressively reduces usable capacity as a function of cumulative use and operating conditions. The time-varying capacity and efficiency enter the energy balance directly, so that the long-term decline in storage performance influences both reliability metrics and lifecycle cost.

3.4 Thermal storage energy balance model

Thermal storage, where included in the configuration, is represented as a finite-capacity reservoir whose internal energy changes according to the net heat transfer from the solar receiver and to the power cycle. Thermal losses to the environment are proportional to the temperature difference between the storage medium and ambient conditions. Charge and discharge rates are constrained by the physical limits of the heat-transfer system. The thermal energy available for conversion to electricity is determined by the storage state and by the efficiency of the power cycle at the prevailing temperature and mass-flow conditions. Progressive degradation of insulation or heat-transfer performance is incorporated as a time-dependent increase in the loss coefficient.

3.5 System-level energy balance equations

At each time step the system energy balance equates the sum of photovoltaic power, wind power and storage discharge to the sum of load, storage charging and curtailment. Unmet load is recorded when generation and available storage discharge are together insufficient to satisfy demand. The balance is evaluated over the full simulation horizon, typically one or more years at hourly or sub-hourly resolution, yielding annual energy production, curtailment fraction, storage utilisation and the time series of unmet load from which reliability indices are derived.

3.6 Reliability and loss-of-power-supply modelling

Reliability is quantified by the loss-of-power-supply probability, defined as the fraction of time steps in which unmet load is positive, and by the expected energy not served, obtained by integrating the magnitude of unmet load over the horizon. These indices are evaluated on the same time series that drive the energy and cost calculations, ensuring consistency among technical, economic and reliability metrics. Designs are required either to satisfy prescribed reliability thresholds as constraints or to treat reliability shortfall as an objective to be minimised.

3.7 Lifecycle cost and emission formulations

Lifecycle cost is expressed as the levelised cost of energy, obtained by dividing the present value of capital, operation, maintenance and replacement costs by the present value of lifetime energy production. Replacement costs associated with degradation-driven capacity loss are included in the cost numerator. Lifecycle greenhouse-gas emissions are calculated by applying published emission factors to the manufactured capacities of each technology and, where appropriate, to operational energy throughputs. Both cost and emission metrics are evaluated over the full analysis horizon and form the economic and environmental objectives of the multi-objective optimisation problem.

IV. MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK

4.1 Decision variables

The decision variables of the optimisation problem correspond to the principal design choices of the hybrid system. These include the rated electrical capacity of the photovoltaic array, the rated power of the wind turbines, the usable energy capacity of the battery storage system and, where applicable, the thermal energy capacity of the storage associated with concentrating solar generation. Selected geometric parameters that exert a first-order influence on performance, such as photovoltaic array tilt angle and wind turbine hub height, may also be treated as continuous decision variables. Discrete variables are introduced when equipment is available only in fixed commercial sizes. Each variable is bounded by physical, commercial or regulatory limits so that the searchable space remains within the domain of engineering feasibility.

4.2 Objective functions

Three conflicting objectives are considered. The economic objective is the minimisation of the levelised cost of energy, which aggregates the present value of capital, operation, maintenance and replacement costs and normalises it by the present value of lifetime energy production. The reliability objective is the minimisation of loss-of-power-supply probability or expected energy not served, thereby reducing the frequency and magnitude of supply shortfalls. The environmental objective is the minimisation of lifecycle greenhouse-gas emissions associated with manufacturing, installation, operation and replacement of system components. Retaining these criteria as separate objectives allows the generation of Pareto-optimal sets that reveal the quantitative trade-offs among cost, reliability and emissions rather than concealing them in a single weighted sum.

4.3 Technical and operational constraints

Technical constraints enforce the physical limits of each component. Instantaneous photovoltaic and wind power cannot exceed the values permitted by the resource and the respective performance models. Storage charge and discharge rates are bounded by manufacturer or thermal limits, and the state of charge or internal energy must remain inside the usable capacity interval. Operational constraints prohibit simultaneous charging and discharging of the same storage unit and

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require curtailment to be non-negative. Reliability constraints may impose an upper bound on loss-of-power-supply probability so that every feasible design meets a minimum standard of supply adequacy. Resource constraints link generation at each time step to the corresponding meteorological series, preventing the creation of energy that the physical resource cannot supply.

4.4 Representation of resource uncertainty

Resource uncertainty is incorporated through a set of representative meteorological scenarios drawn from multi-year records or generated by statistical sampling that preserves the observed temporal correlation structure and the cross-correlation between solar and wind resources. For each candidate design the system model is evaluated on every scenario. Objectives and reliability metrics are then aggregated either as expected values over the scenario set or as robust measures that protect against adverse realisations. This approach ensures that optimised designs are assessed not only under average conditions but under the range of resource sequences that the system is likely to encounter over its operating life.

4.5 Incorporation of component degradation

Component degradation is introduced as a time-dependent reduction in the performance parameters of each technology. Photovoltaic modules experience a progressive loss of nominal power; wind turbine power curves shift as a result of blade soiling and erosion; and battery usable capacity declines with cumulative energy throughput and calendar ageing. These modifiers are updated over the simulation horizon and influence both the energy balance and the cost calculations that include replacement expenditures. By embedding degradation directly within the performance models, the optimisation anticipates the lifetime trajectory of system output rather than assuming constant as-new behaviour.

4.6 Complete mathematical problem statement

The multi-objective optimisation problem is stated as the simultaneous minimisation of the economic, reliability and environmental objective functions subject to the technical, operational and reliability constraints and to the bounds on the decision variables. Each objective is an aggregation over the simulation horizon of instantaneous cost, unmet-load or emission quantities that depend on the decision vector through the physical component models and the system-level energy balance. The solution of the problem is the set of non-dominated designs that constitute the Pareto front, from which decision-makers may select according to additional preferences regarding the relative importance of cost, reliability and environmental performance.

V. SOLUTION APPROACH

5.1 Selection of multi-objective algorithms

The optimisation problem formulated in the preceding section is non-linear, non-convex and mixed continuous–discrete, with objective and constraint evaluations requiring time-series simulation under multiple resource scenarios. Gradient-based methods are therefore unsuitable for the full problem without extensive reformulation. Multi-objective evolutionary algorithms are selected as the primary solution approach because they require no derivative information, can accommodate discrete variables and discontinuous reliability metrics, and return an approximation of the entire Pareto front rather than a single point. Non-dominated sorting genetic algorithm II and related variants are employed for their established performance in generating well-distributed non-dominated sets. Hybrid memetic extensions that combine evolutionary search with local refinement are also considered to improve convergence and front coverage. For comparative purposes, selected single-objective metaheuristics are applied to scalarised versions of the problem, and classical mathematical programming methods are used on convexified sub-problems to provide reference solutions.

5.2 Algorithm configuration and control parameters

Population size, number of generations, crossover and mutation rates, and archive management parameters are assigned nominal values based on established practice for problems of comparable dimensionality and are refined through preliminary trials on reduced test cases. The same computational budget, measured in the number of high-fidelity function evaluations, is imposed on every algorithm to ensure fair comparison. Stochastic methods are executed for multiple independent runs with different random seeds, and summary statistics of solution quality and front indicators are reported together with measures of dispersion. Constraint handling is performed through penalty functions or through the native mechanisms of the chosen algorithms, preserving the physical meaning of every constraint.

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5.3 Computational implementation
The computational framework is organised as a modular pipeline linking data preparation, physical model evaluation, optimisation and post-processing. Meteorological time series, component parameter libraries and scenario sets are managed in a data layer. The model layer encapsulates the photovoltaic, wind, storage and energy-balance calculations, accepting a decision vector and returning objective and constraint values. The optimisation layer invokes the selected algorithms and repeatedly calls the model layer. Parallel evaluation of independent design candidates is supported to reduce wall-clock time. Version control, explicit random seeding and archival of intermediate results are maintained to ensure reproducibility of the numerical experiments.

5.4 Performance metrics for solution evaluation
Solution quality for multi-objective runs is assessed through hypervolume, which measures the volume of objective space dominated by the obtained front, and through spacing and extent indicators that characterise the distribution of solutions along the front. For single-objective comparisons, the final objective value and its statistical stability across repeated runs are recorded. Computational efficiency is expressed as the quality achieved per high-fidelity evaluation and as the wall-clock time required to reach prescribed quality thresholds. These metrics enable a transparent ranking of the algorithmic approaches under identical experimental conditions.

VI. RESULTS AND ANALYSIS

6.1 Resource characterization of the study location
The study location is characterised by a high solar resource with pronounced seasonal variation. Global horizontal irradiance reaches peak monthly averages in the pre-monsoon and early summer months under predominantly clear-sky conditions, followed by a reduction during the monsoon associated with increased cloud cover and a higher diffuse fraction. Post-monsoon recovery restores elevated irradiance levels, although shortening day lengths moderate daily totals through autumn and winter. The wind resource is moderate in mean speed yet exhibits temporal patterns that partially complement solar generation, particularly during evening hours and portions of the monsoon season. Statistical analysis of daily and multi-day variability identifies sequences of consecutive low-resource days that define the characteristic drought durations relevant to storage sizing and reliability assessment. Joint distributions of solar irradiation and wind speed confirm seasonally dependent correlation structures that are retained in the scenario ensembles used for uncertainty-aware optimisation.

6.2 Optimal capacity allocation results
Multi-objective optimisation yields non-dominated designs in which photovoltaic capacity constitutes the largest share of installed generation, consistent with the high specific yield of the solar resource at the study location. Wind capacity appears at lower absolute levels but is retained across a substantial portion of the Pareto front, indicating that its complementary temporal profile justifies inclusion even when stand-alone capacity factors are moderate. Battery storage capacity varies systematically with the reliability target: higher supply-adequacy requirements lead to larger storage volumes. When thermal storage is admitted, a portion of the storage allocation shifts toward the thermal option in designs that prioritise dispatchability. Explicit representation of degradation produces a modest increase in initial generation and storage capacities relative to constant-performance optimisations, ensuring that end-of-life performance remains within the reliability envelope.

6.3 Energy contribution of each technology
Photovoltaic generation supplies the dominant fraction of annual energy in the optimised hybrids, with the highest contribution occurring during clear-sky summer and autumn periods and a reduced share during the monsoon. Wind generation contributes a smaller but persistent fraction of annual energy, with elevated relative importance during evening hours and monsoon intervals when solar output declines. Storage discharge redistributes energy from periods of surplus to periods of deficit and accounts for a material share of load satisfaction, particularly in the post-sunset period. The seasonal and diurnal evolution of these contribution shares confirms the complementary roles of the three technology classes and demonstrates that annual energy fractions alone do not fully capture the reliability value of wind and storage.

6.4 Reliability performance of optimized designs
Designs lying on the high-reliability region of the Pareto front achieve loss-of-power-supply probabilities at or below the prescribed constraint thresholds. Residual unmet-load events are concentrated during the most severe multi-day resource

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droughts, when simultaneous low irradiance and low wind speed exhaust available storage. Hybrid configurations that combine photovoltaic and wind generation reach a given reliability target with smaller storage volumes than pure photovoltaic–battery systems, quantifying the storage-saving benefit of resource complementarity. Increasing storage capacity and generation overbuild reduces both the frequency and the magnitude of residual shortfalls, tracing a clear reliability–cost frontier.

6.5 Economic and environmental indicators

Levelised cost of energy rises with the stringency of the reliability constraint, reflecting the additional capital expenditure required for higher generation and storage capacities. Photovoltaic-dominated hybrids occupy the lower-cost region of the frontier under the adopted resource and cost assumptions. The inclusion of wind capacity improves the cost–reliability trade-off by reducing the storage volume needed for a given reliability target. Lifecycle greenhouse-gas emissions remain substantially below those of fossil-dominated supply. Designs that minimise emissions favour higher photovoltaic and wind fractions and limit oversized storage, whereas designs that prioritise reliability accept higher embodied emissions associated with additional capacity and storage.

6.6 Pareto front analysis

The obtained Pareto fronts exhibit a characteristic shape in the cost–reliability plane: a steep segment at lower cost in which modest additional expenditure purchases substantial reliability gains, followed by a flatter segment in which further improvements become progressively more expensive. The knee region of the front identifies designs that offer a balanced compromise between economic and reliability objectives. Introduction of the environmental objective expands the front into a surface whose extremities correspond to low-emission and high-reliability designs, respectively. Fronts generated under uncertainty-aware formulations lie outward from their deterministic counterparts, indicating that robustness is purchased at the cost of higher levelised cost and, in some cases, residual unmet load.

6.7 Effect of uncertainty on optimal solutions

When multi-year resource ensembles that emphasise prolonged low-resource sequences are substituted for the base-case meteorological data, optimal storage volumes and generation margins increase. Levelised cost rises by a quantifiable robustness premium relative to deterministic optima. Reliability indices deteriorate for designs sized under typical-year assumptions when those designs are evaluated under adverse ensembles, confirming that deterministic optimisation under-states the capacity required for robust performance. Diversified hybrids that retain both photovoltaic and wind capacity exhibit smaller performance degradation under resource stress than single-technology configurations.

6.8 Effect of degradation on long-term performance

Accelerated degradation rates reduce lifetime energy production and cause year-by-year deterioration of reliability indices when capacities are held fixed at their initial values. Optimisation runs that anticipate higher degradation respond by increasing initial generation and storage capacities, preserving end-of-life reliability at the expense of higher capital cost and levelised cost. The magnitude of the capacity uplift scales with the degradation rate of the affected components. Omission of degradation therefore produces designs that appear economical under as-new assumptions but that fail to maintain target reliability over the full analysis horizon.

6.9 Sensitivity analysis of key parameters

Sensitivity experiments identify storage capacity and generation overbuild as the parameters with the strongest influence on reliability indices. Photovoltaic capital cost variation induces substitution between photovoltaic capacity and alternative generation or storage options, while battery cost variation primarily affects the storage volume selected for a given reliability target. Discount rate changes act as a global filter on capital intensity, with higher rates favouring leaner designs and lower rates favouring more heavily buffered configurations. Interaction effects are material: the reliability penalty of accelerated degradation is amplified under adverse resource conditions, and the reliability benefit of additional storage is greater when generation overbuild is limited. Overall robustness is highest for diversified hybrid designs that incorporate a storage margin above the deterministic optimum.

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VII. DISCUSSION

7.1 Interpretation of optimization outcomes

The optimisation results show that hybrid solar–wind–storage systems can achieve high supply reliability at competitive levelised costs under the modelled high-irradiance conditions when capacities are allocated according to multi-objective criteria. Photovoltaic capacity dominates the non-dominated designs because of its high specific yield and favourable economics, while wind capacity is retained at lower levels for its complementary temporal contribution. Storage emerges as the principal instrument for purchasing reliability: larger storage volumes reduce loss-of-power-supply probability, yet the marginal benefit diminishes once autonomy exceeds the characteristic duration of resource droughts. The Pareto fronts make these trade-offs explicit, allowing designs to be selected according to the relative importance attached to cost, reliability and emissions.

7.2 Influence of mechanical modelling on results

The use of first-principles mechanical models rather than static efficiency curves has a direct influence on the optimised designs. Temperature derating, soiling, aerodynamic power-curve behaviour, thermal losses and progressive capacity fade alter both the absolute energy yields and the relative value of each technology. Designs obtained under simplified constant-performance assumptions under-estimate the capacity and storage margins required to maintain long-term reliability and produce optimistic levelised-cost projections. By retaining physical mechanisms inside the optimisation loop, the framework ensures that decision variables remain interpretable in engineering terms and that the predicted performance reflects the dominant loss and ageing processes encountered in field operation.

7.3 Trade-offs among cost, reliability and emissions

The multi-objective results confirm that cost, reliability and emissions cannot be improved simultaneously without compromise. Higher reliability targets require additional generation and storage, elevating both capital cost and embodied emissions. Low-emission designs favour higher photovoltaic and wind fractions and limit oversized storage, accepting a modest residual unmet load. The knee region of the cost–reliability front identifies configurations that offer a balanced compromise, while the extremities of the front correspond to cost-driven and reliability-driven extremes. These quantitative trade-offs provide a transparent basis for design selection under different institutional or project-specific priorities.

7.4 Comparison with simplified optimization approaches

Comparison with deterministic optimisations that omit degradation and resource uncertainty shows systematic differences. Deterministic constant-performance designs employ smaller storage volumes and generation margins and report lower levelised costs. When the same designs are evaluated under multi-year adverse resource ensembles and progressive degradation, reliability indices deteriorate and lifetime energy yield falls below projections. Uncertainty-aware and degradation-aware formulations produce more conservative capacity allocations and higher levelised costs, but they maintain target reliability over the analysis horizon. The difference quantifies the premiums associated with lifetime realism and robustness and demonstrates the limitations of simplified approaches for long-term system design.

7.5 Practical design implications

The findings support several practical recommendations for the design of hybrid solar–wind–storage systems. Photovoltaic generation should form the primary capacity under high-irradiance conditions, supplemented by a non-zero wind allocation to exploit temporal complementarity and reduce storage requirements. Storage should be sized according to observed drought durations and target reliability levels rather than average-load rules of thumb. Explicit allowance for progressive degradation in the initial capacity vector is economically justified and prevents under-performance at end of life. When planners are accountable for multi-year resource stress, a moderate robustness margin relative to deterministic optima is warranted. Algorithmic choice should be matched to problem structure, with multi-objective evolutionary and hybrid methods preferred for generating trade-off surfaces and surrogate assistance employed when high-fidelity evaluations are computationally expensive.

VIII. CONCLUSION

This paper has presented a mechanically grounded multi-objective optimisation framework for hybrid solar–wind–storage systems that incorporates first-principles component models, progressive degradation and resource uncertainty.

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Detailed mathematical models of photovoltaic arrays, wind turbines and storage units were developed and embedded within a multi-objective formulation minimising lifecycle cost and greenhouse-gas emissions while improving supply reliability. Numerical experiments under high-irradiance conditions showed that photovoltaic-dominated hybrids with complementary wind capacity and appropriately sized storage achieve favourable cost–reliability trade-offs. Explicit treatment of degradation and multi-year resource uncertainty increased optimal storage and generation margins and elevated levelised cost relative to deterministic constant-performance assumptions, quantifying the premiums associated with lifetime realism and robustness. Pareto front analysis revealed clear trade-offs among cost, reliability and emissions, and sensitivity experiments identified storage capacity, generation overbuild and degradation rate as the parameters with the strongest influence on system performance.

The principal contribution of the work is the integration of mechanically interpretable component models with multi-objective optimisation under degradation and uncertainty within a single coherent framework. Decision variables retain clear physical meaning, performance predictions reflect dominant loss and ageing mechanisms, and the resulting designs are more robust and more credible for long-term engineering application than those obtained under simplified assumptions. The comparative evaluation of solution algorithms further provides practical guidance on the selection of methods matched to problem structure, while the location-grounded numerical results supply quantitative evidence relevant to high-resource deployment environments.

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