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Optimal Design of Hybrid Renewable Energy Systems Using First-Principles Mechanical Models and Multi-Objective Evolutionary Algorithms

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ABSTRACT: The optimal design of hybrid renewable energy systems is frequently performed using simplified efficiency curves that weaken the link between component-level physical behaviour and system-level performance. This paper presents an optimal design framework that integrates first-principles mechanical models of solar photovoltaic, wind turbine and energy storage components with multi-objective evolutionary algorithms. Detailed models are developed to capture optical and thermal effects in photovoltaic arrays, aerodynamic power characteristics of horizontal-axis wind turbines, and charge–discharge dynamics together with capacity fade in storage systems. These models are embedded in a multi-objective formulation that simultaneously minimises lifecycle cost and greenhouse-gas emissions while improving supply reliability. Non-dominated sorting genetic algorithm II and related evolutionary methods are employed to generate Pareto-optimal sets of hybrid system designs. Numerical results demonstrate that designs obtained with first-principles models differ systematically from those produced under constant-performance assumptions, particularly in storage sizing and long-term reliability margins. Photovoltaic-dominated hybrids with complementary wind capacity and appropriately sized storage achieve favourable trade-offs among cost, reliability and environmental performance. The study confirms that coupling mechanically grounded component models with multi-objective evolutionary search improves both the physical credibility and the practical usefulness of optimised hybrid renewable energy system designs.

KEYWORDS: Hybrid renewable energy systems; First-principles mechanical models; Multi-objective evolutionary algorithms; Optimal design; Solar–wind–storage systems; Pareto optimization; Lifecycle cost; Supply reliability.

I. INTRODUCTION

1.1 Background of hybrid renewable energy systems

Hybrid renewable energy systems that combine solar photovoltaic generation, wind power and energy storage have become a central option for improving the reliability and economic performance of renewable-based power supply. By exploiting the complementary temporal patterns of solar and wind resources and by shifting excess energy through storage, hybrid configurations can reduce curtailment, raise capacity factors and lower the residual unmet load compared with single-technology plants. The rapid decline in the cost of photovoltaic modules, wind turbines and battery storage has further increased the practical relevance of such systems for both off-grid and grid-supported applications.

1.2 Limitations of simplified efficiency-based optimization approaches

A large body of optimization studies sizes hybrid systems using constant efficiency factors or manufacturer power curves treated as static input data. While computationally convenient, these simplified representations detach the optimisation outcome from the underlying physical processes that govern real component behaviour. Temperature-dependent efficiency losses, soiling, aerodynamic performance variation with wind speed, thermal losses in storage and progressive capacity fade are either omitted or introduced only as fixed correction coefficients. Consequently, the resulting capacity allocations may appear economical under idealised assumptions yet under-perform when exposed to realistic operating conditions and long-term ageing.

1.3 Importance of first-principles mechanical modelling

First-principles mechanical models restore the connection between component physics and system-level design decisions. Photovoltaic output can be expressed through optical absorption, energy balance for module temperature and temperature-corrected electrical conversion. Wind turbine power can be obtained from aerodynamic rotor theory or

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validated power curves that respect cut-in, rated and cut-out regimes together with air-density effects. Storage behaviour can be described by state-of-charge dynamics, round-trip efficiency and capacity fade driven by energy throughput. When these representations are retained inside the optimisation loop, the decision variables retain clear engineering meaning and the predicted performance reflects the dominant loss and degradation mechanisms encountered in practice.

1.4 Role of multi-objective evolutionary algorithms

Hybrid system design involves conflicting criteria—lifecycle cost, supply reliability and environmental impact—that cannot be collapsed into a single metric without concealing important trade-offs. Multi-objective evolutionary algorithms are well suited to this class of problem because they require no gradient information, accommodate non-linear and discontinuous performance metrics, and return a set of non-dominated solutions that approximate the Pareto front. Non-dominated sorting genetic algorithm II and related methods have demonstrated robust performance in generating well-distributed fronts for hybrid renewable sizing problems and are therefore adopted as the principal solution approach.

II. HYBRID SYSTEM CONFIGURATION

2.1 Overall system architecture

The hybrid renewable energy system examined in this study integrates solar photovoltaic generation, wind energy conversion and energy storage to meet a prescribed electrical load. At each time step the combined output of the photovoltaic array and the wind turbines is compared with the instantaneous load. Surplus generation is directed to storage charging within the limits of storage capacity and power rating, while energy deficits are covered first by storage discharge. Any remaining shortfall is recorded as unmet load, and excess generation that cannot be stored is curtailed. This architecture allows the complementary temporal characteristics of solar and wind resources to be exploited while storage provides temporal shifting of energy.

2.2 Solar photovoltaic subsystem

The photovoltaic subsystem consists of module arrays characterised by rated capacity under standard test conditions, temperature coefficient, and optical and thermal behaviour. Instantaneous power output depends on the effective plane-of-array irradiance, module operating temperature and soiling state. Array tilt angle and orientation influence the intercepted irradiance and are treated as fixed or optimisable geometric parameters according to the design case. Long-term reduction in nominal power caused by progressive degradation is included so that lifetime energy yield reflects realistic ageing.

2.3 Wind energy conversion subsystem

The wind energy conversion subsystem comprises horizontal-axis wind turbines whose electrical output is determined by the hub-height wind speed through the turbine power curve. The power curve incorporates cut-in, rated and cut-out regimes. Hub-height wind speed is obtained from surface measurements by means of a shear profile, and air-density corrections are applied. Availability factors account for scheduled maintenance and forced outages. Gradual performance loss associated with blade soiling and leading-edge erosion is represented as a progressive modification of the power curve over the system lifetime.

2.4 Energy storage subsystem

Energy storage is provided primarily by electrochemical battery banks. The storage unit is characterised by usable energy capacity, charge and discharge efficiencies, maximum power limits and state-of-charge bounds. The state of charge is updated at each time step according to the net energy transferred, corrected for round-trip losses. Capacity fade arising from cumulative energy throughput is included so that usable storage capacity declines over the analysis horizon. Where thermal storage is considered in conjunction with solar thermal generation, an energy-balance model with thermal losses is employed.

2.5 Load demand and energy management strategy

The electrical load is represented by a time series of power demand that the hybrid system is required to satisfy. The energy management strategy follows a priority order: renewable generation first meets the load, surplus generation charges storage, and storage discharge covers residual deficits. Simultaneous charging and discharging of the same storage unit is not permitted. The resulting time series of generation, storage exchange, curtailment and unmet load form

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the basis for calculating annual energy production, reliability indices and lifecycle performance metrics used in the optimisation.

III. FIRST-PRINCIPLES MECHANICAL MODELLING

3.1 Photovoltaic optical, thermal and electrical model

The photovoltaic power output is obtained from a coupled optical–thermal–electrical representation. Effective irradiance on the plane of the array is determined after accounting for incidence-angle modifiers and soiling losses. Module operating temperature is calculated from a quasi-steady energy balance that includes absorbed solar radiation, convective and radiative heat exchange with the surroundings, and the fraction of incident energy converted to electricity. Electrical power is then evaluated from the rated capacity under standard test conditions, corrected by the temperature coefficient and the effective irradiance ratio. Progressive degradation is introduced as a time-dependent reduction in nominal power, so that annual energy yield declines over the system lifetime in a manner consistent with field observations.

3.2 Wind turbine aerodynamic power model

Wind turbine output is determined by mapping hub-height wind speed onto the aerodynamic power curve of the machine. Below cut-in speed the power is zero; between cut-in and rated speed the power follows a cubic or empirically calibrated function of wind speed; between rated and cut-out speed the output is regulated at the rated value; and above cut-out speed the turbine is shut down. Hub-height wind speed is estimated from near-surface measurements using a power-law or logarithmic shear profile. Air-density corrections are applied to account for temperature and site elevation. Availability losses and gradual performance reduction caused by blade surface degradation are incorporated as multiplicative and time-dependent modifiers on the ideal power curve.

3.3 Battery storage model with capacity fade

The battery storage system is described by a state-of-charge integrator subject to capacity limits, charge and discharge efficiencies, and maximum power ratings. The change in state of charge at each time step is calculated from the net energy transferred to or from the battery, adjusted for round-trip losses. Capacity fade is modelled as a progressive reduction in usable capacity driven by cumulative energy throughput and, where data permit, by calendar ageing. The time-varying capacity enters the energy balance directly, ensuring that the long-term decline in storage performance influences both reliability metrics and lifecycle cost.

3.4 Thermal storage energy balance model

When thermal storage is included, its state is governed by an energy balance that accounts for heat input from the solar receiver, heat extraction by the power cycle, and thermal losses to the environment. Losses are expressed as a function of 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 depends on the storage state and on the efficiency of the power cycle at the prevailing operating conditions.

3.5 System-level energy balance formulation

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 whenever generation and available storage discharge are insufficient to meet demand. The balance is evaluated over the full simulation horizon, yielding the annual energy production, curtailment fraction and the time series of unmet load required for reliability assessment.

3.6 Reliability indices

Supply 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. Both indices are computed from the same energy-balance time series that drive the cost and emission calculations, ensuring consistency among the technical and economic performance metrics.

3.7 Lifecycle cost and emission models

Lifecycle cost is expressed as the levelised cost of energy, formed 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 numerator. Lifecycle greenhouse-gas emissions are calculated by applying emission factors to the installed capacities of each technology and, where appropriate, to operational energy flows. These economic and environmental metrics constitute the objective functions of the multi-objective optimisation problem.

IV. MULTI-OBJECTIVE OPTIMIZATION FORMULATION

4.1 Decision variables

The decision variables represent the principal design choices of the hybrid system. They include the rated capacity of the photovoltaic array, the rated power of the wind turbines and the usable energy capacity of the battery storage system. Where thermal storage is considered, its energy capacity is also treated as a decision variable. Selected geometric parameters that influence performance, such as photovoltaic array tilt angle or wind-turbine hub height, may be included as continuous variables when their effect is significant. Each variable is bounded by physical, commercial or practical limits so that only feasible designs are examined.

4.2 Objective functions

Three conflicting objectives are formulated. The economic objective minimises 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 minimises the loss-of-power-supply probability or the expected energy not served, thereby reducing the frequency and magnitude of supply shortfalls. The environmental objective minimises lifecycle greenhouse-gas emissions associated with the manufacture, installation and replacement of system components. Retaining the three criteria as separate objectives allows the full set of trade-offs to be examined through the Pareto front.

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 the rated power of the storage unit, and the state of charge must remain inside the usable capacity interval. Operational constraints prohibit simultaneous charging and discharging of the same storage device and require curtailment to be non-negative. Reliability constraints may impose an upper limit on loss-of-power-supply probability so that every feasible design satisfies a minimum standard of supply adequacy. Resource constraints link generation at each time step to the corresponding meteorological data.

4.4 Mathematical statement of the optimization problem

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 evaluated from the time-series simulation of the hybrid system under the first-principles component models. The solution of the problem is the set of non-dominated designs that approximate the Pareto front, from which a final configuration may be selected according to the relative importance attached to cost, reliability and environmental performance.

V. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

5.1 Selection of evolutionary algorithms

The optimisation problem is non-linear and non-convex, with objective and constraint values obtained from time-series simulation of the hybrid system. Gradient-based methods are therefore unsuitable without extensive reformulation. Multi-objective evolutionary algorithms are selected because they operate without derivative information, accommodate discrete and continuous decision variables, and return an approximation of the entire Pareto front. Non-dominated sorting genetic algorithm II is adopted as the primary solution method on account of its established performance in generating well-distributed non-dominated sets for hybrid renewable sizing problems. Related evolutionary variants and hybrid memetic extensions that combine population-based search with local refinement are also examined for comparative purposes.

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5.2 Non-dominated sorting and diversity preservation mechanisms

Non-dominated sorting ranks individuals according to Pareto dominance depth, assigning the highest rank to solutions that are not dominated by any other member of the population. Crowding distance is used to preserve diversity along the front by favouring solutions located in less densely populated regions of objective space. Elitism ensures that the best non-dominated individuals are retained from one generation to the next. These mechanisms together promote both convergence toward the true Pareto front and adequate coverage of the trade-off surface among cost, reliability and emissions.

5.3 Algorithm parameter settings

Population size, number of generations, crossover probability and mutation rate are assigned values consistent with established practice for problems of comparable dimensionality. The same computational budget, expressed as the number of high-fidelity function evaluations, is applied across algorithmic variants to permit fair comparison. Stochastic runs are repeated with different random seeds, and summary statistics of front quality are recorded to assess the stability of the obtained results. Constraint handling is performed through penalty functions or through the native ranking mechanisms of the algorithm, preserving the physical meaning of every constraint.

5.4 Solution evaluation metrics

The quality of the obtained Pareto fronts is assessed by hypervolume, which measures the volume of objective space dominated by the non-dominated set relative to a reference point, and by spacing and extent indicators that characterise the distribution of solutions along the front. These metrics enable quantitative comparison of algorithmic performance and support the selection of the final set of optimised designs used for subsequent analysis.

VI. RESULTS AND ANALYSIS

6.1 Resource data and system parameters

The numerical experiments are conducted using multi-year meteorological records of solar irradiance, ambient temperature and wind speed representative of a high-irradiance location. Photovoltaic, wind turbine and battery storage parameters are taken from manufacturer data and calibrated literature values, including temperature coefficients, power-curve coefficients, charge–discharge efficiencies and degradation rates. Load demand is represented by a prescribed annual time series. All simulations are performed at hourly resolution over the full analysis horizon so that diurnal and seasonal variability are retained.

6.2 Optimal capacity allocation

Multi-objective optimisation produces non-dominated designs in which photovoltaic capacity forms the largest share of installed generation, consistent with the high solar resource. Wind capacity appears at lower absolute levels yet is retained across a substantial portion of the Pareto front, indicating that its complementary generation profile justifies inclusion. Battery storage capacity increases systematically with the stringency of the reliability requirement. Designs obtained with first-principles models and explicit degradation incorporate modestly larger generation and storage capacities than those produced under constant-performance assumptions, reflecting the need to maintain end-of-life reliability.

6.3 Energy contribution of individual technologies

Photovoltaic generation supplies the dominant fraction of annual energy, with the highest contribution during clear-sky periods and a reduced share during intervals of lower irradiance. Wind generation contributes a smaller but persistent fraction of annual energy, with elevated relative importance during evening hours and periods of reduced solar output. Storage discharge redistributes surplus energy to periods of deficit and accounts for a material share of load satisfaction, particularly after sunset. The temporal distribution of these contributions confirms the complementary roles of the three technology classes.

6.4 Reliability performance of optimized designs

Designs located on the high-reliability region of the Pareto front achieve loss-of-power-supply probabilities at or below the prescribed thresholds. Residual unmet-load events are concentrated during the most severe multi-day resource shortfalls. Hybrid configurations that include both photovoltaic and wind generation reach a given reliability target with smaller storage volumes than pure photovoltaic–battery systems, demonstrating the storage-saving benefit of resource

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complementarity. Increasing storage capacity and generation margin reduces both the frequency and the magnitude of residual shortfalls.

6.5 Economic and environmental performance
Levelised cost of energy rises with the reliability target, reflecting the additional capital expenditure required for larger generation and storage capacities. Photovoltaic-dominated hybrids occupy the lower-cost region of the front 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 level. Lifecycle greenhouse-gas emissions remain substantially lower than those of fossil-based supply. Designs that prioritise low emissions favour higher renewable fractions and limit oversized storage, while designs that prioritise reliability accept higher embodied emissions associated with additional capacity.

6.6 Pareto front characteristics
The obtained Pareto fronts display a characteristic shape in the cost–reliability plane: a steep segment at lower cost in which modest additional expenditure yields substantial reliability gains, followed by a flatter segment in which further improvements become progressively more expensive. The knee region identifies designs that offer a balanced compromise between the competing objectives. Fronts generated with first-principles models and degradation lie outward from those obtained under simplified constant-performance assumptions, indicating that physical realism is purchased at a quantifiable cost premium.

6.7 Influence of mechanical modelling fidelity on results
Comparison of designs obtained with first-principles models against those obtained with static efficiency curves reveals systematic differences. Simplified models under-estimate storage and generation margins required for long-term reliability and produce lower levelised-cost projections. When the same simplified designs are evaluated with the detailed mechanical models, reliability indices deteriorate and lifetime energy yield falls below the original predictions. Retention of temperature effects, soiling, aerodynamic behaviour and capacity fade therefore alters both the absolute performance metrics and the relative ranking of candidate configurations.

6.8 Sensitivity analysis
Sensitivity experiments show that storage capacity and generation overbuild exert the strongest influence on reliability indices. Variation of photovoltaic capital cost induces substitution between photovoltaic capacity and alternative generation or storage options. Higher degradation rates increase the initial capacity margin required to maintain end-of-life reliability and elevate levelised cost. 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. Overall robustness is highest for diversified hybrids that combine photovoltaic and wind generation with a storage margin above the deterministic optimum.

VII. DISCUSSION

7.1 Interpretation of optimal design outcomes
The optimisation results demonstrate that hybrid solar–wind–storage systems can deliver high supply reliability at competitive levelised costs when capacities are allocated through a multi-objective process grounded in first-principles component models. Photovoltaic capacity dominates the non-dominated designs because of its high specific yield under the modelled resource conditions, while wind capacity is retained at lower levels for its complementary temporal contribution. Storage capacity emerges as the principal means of purchasing reliability: larger storage volumes reduce loss-of-power-supply probability, yet the marginal benefit diminishes once storage autonomy exceeds the characteristic duration of resource shortfalls. The Pareto fronts make these trade-offs explicit and allow designs to be selected according to the relative weight attached to cost, reliability and emissions.

7.2 Advantage of first-principles models over simplified approaches
Comparison with designs obtained under constant-efficiency assumptions confirms the practical value of retaining mechanical component models inside the optimisation loop. Simplified models under-estimate the storage and generation margins required to maintain long-term reliability and produce optimistic levelised-cost projections. When the same simplified designs are re-evaluated with the first-principles models, reliability indices deteriorate and lifetime energy

yield declines. Temperature derating, soiling, aerodynamic power-curve behaviour and progressive capacity fade therefore act as first-order influences on optimal capacity allocation. By preserving these mechanisms, the framework ensures that decision variables remain interpretable in engineering terms and that predicted performance remains consistent with the physical processes that govern real operation.

7.3 Performance of multi-objective evolutionary algorithms
Non-dominated sorting genetic algorithm II and related evolutionary methods prove effective in generating well-distributed Pareto fronts for the hybrid sizing problem. The combination of non-dominated sorting and crowding-distance diversity preservation produces fronts that adequately cover the trade-off surface among cost, reliability and emissions. Hybrid memetic extensions that apply local refinement to selected individuals further improve convergence and front coverage. The algorithmic results support the use of multi-objective evolutionary search as a practical solution approach for non-linear, simulation-based hybrid renewable design problems that incorporate detailed mechanical models.

7.4 Practical design implications
The findings support several practical recommendations for the design of hybrid renewable energy 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 resource-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 the end of the analysis horizon. Designers who adopt first-principles component models within a multi-objective evolutionary framework obtain capacity allocations that are more robust and more physically credible than those produced by simplified efficiency-based methods.

VIII. CONCLUSION

This paper has presented an optimal design framework for hybrid renewable energy systems that couples first-principles mechanical models of photovoltaic, wind and storage components with multi-objective evolutionary algorithms. Detailed representations of optical and thermal behaviour, aerodynamic power conversion, storage dynamics and progressive capacity fade were embedded within a multi-objective formulation minimising lifecycle cost and greenhouse-gas emissions while improving supply reliability. Numerical results showed that photovoltaic-dominated hybrids with complementary wind capacity and appropriately sized storage achieve favourable trade-offs among cost, reliability and environmental performance. Designs obtained with first-principles models incorporate larger storage and generation margins than those produced under constant-performance assumptions, reflecting the influence of temperature effects, soiling, aerodynamic behaviour and degradation on long-term system performance.

The principal contribution of the work is the demonstration that first-principles mechanical models can be integrated productively with multi-objective evolutionary search for hybrid renewable system design. The resulting capacity allocations retain clear engineering meaning, reflect dominant physical loss and ageing mechanisms, and differ systematically from designs obtained with simplified efficiency curves. The framework therefore strengthens the link between component-level mechanical behaviour and system-level optimisation outcomes.

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