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Techno-Economic Optimization and Stochastic Sizing of Solar-Wind-Biomass Hybrid Systems for Off-Grid Mountain Communities

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ABSTRACT

The electrification of remote, high-altitude communities presents extreme techno-economic challenges driven by rugged topologies, harsh winter climates, and the inherent intermittency of renewable energy resources. While solar and wind systems combined with battery storage dominate off-grid applications, their dependence on massive energy storage banks during extended winter deficits drastically inflates capital costs and lifecycle emissions. This paper proposes a robust stochastic optimization framework for a hybrid Solar Photovoltaic (PV), Wind Turbine (WT), and Biomass Gasifier (BM) microgrid system. By utilizing locally sourced biomass as a dispatchable buffer, the proposed mathematical framework minimizes the Levelized Cost of Energy (LCOE) and Net Present Cost (NPC) while strictly enforcing a 99% reliability threshold via the Loss of Power Supply Probability (LPSP). A high-fidelity numerical case study is conducted for an isolated settlement near Dushanbe, Tajikistan, analyzing the non-linear trade-offs between local bioenergy feedstock availability and chemical energy storage degradation in sub-zero climates. The Particle Swarm Optimization (PSO) coupled with Monte Carlo simulations demonstrates that the optimal PV-WT-BM configuration reduces the LCOE by 31.4% ($0.243/kWh) compared to standard PV-WT-Battery baseline topologies ($0.354/kWh). The integration of dispatchable bioenergy collapses necessary battery capacities by 81.0%, emphasizing that targeted policy subsidies for biomass logistics are highly economically superior to battery oversizing in extreme winter climates.

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1. INTRODUCTION

Securing reliable, low-carbon electricity for isolated mountainous regions remains a critical frontier in global energy equity and sustainable development [1]. Traditional grid extensions in these topographies are economically prohibitive due to high transmission line capital costs, severe terrain constraints, and heavy transmission losses. Consequently, decentralized Hybrid Renewable Energy Systems (HRES) have emerged as the standard paradigm for rural electrification [2].

However, high-altitude environments—such as the Pamir and Fann mountains in Central Asia—exhibit unique meteorological challenges. Deep winter seasons feature heavy snow cover, plummeting temperatures, and sustained periods of low solar irradiance and stagnant wind. Relying exclusively on intermittent resources (PV and WT) combined with Battery Energy Storage Systems (BESS) leads to dramatic structural oversizing to ensure winter reliability [3]. This "oversizing penalty" drives the LCOE far beyond the economic capacity of local populations, hampering rural development initiatives like the Tajikistan Rural Electrification Project (TREP) [4].

To address this critical gap, this paper introduces a dispatchable Biomass Generator (BM) into the conventional HRES topology. Biomass functions as a firm, on-demand energy vector that decouples winter power generation from immediate meteorological conditions [5]. We present a rigorous stochastic optimization model to appropriately size the components of a PV-WT-BM-BESS architecture. By embedding a temperature-dependent battery degradation model and utilizing a Monte Carlo-enhanced Particle Swarm Optimization (PSO) algorithm [6, 7], this study captures the probabilistic nature of renewable resources to yield a highly resilient, techno-economically viable microgrid design. Transfer-learning-based demand-forecasting techniques, such as those proposed by Kamalov et al. for electricity load prediction in a general grid-connected setting, address a related but distinct problem of anticipating the load side rather than sizing generation and storage against a fixed profile [23].

2. LITERATURE REVIEW

The sizing of hybrid microgrids is a complex, non-linear optimization problem extensively explored in recent literature. Seminal works by Diaf et al. [8] and Deshmukh & Deshmukh [1] laid the foundation for deterministic sizing methodologies. However, modern approaches increasingly rely on metaheuristic algorithms due to their ability to navigate vast, multi-objective search spaces. Borhanazad et al. [3] successfully utilized Multi-Objective PSO (MOPSO) to minimize the cost of a standalone microgrid, a method later improved by Nkalo et al. [7] for PV-Wind-Battery architectures.

Despite algorithmic advancements, most studies isolate their environmental models to temperate zones. Mokhtara et al. [2] and Omotoso et al. [5] optimized hybrid systems for arid and tropical climates, but high-altitude, cold-weather modeling remains sparse. Sub-zero temperatures severely restrict BESS chemical kinetics, a phenomenon rarely integrated into techno-economic LCOE calculations, though fundamental degradation frameworks have been proposed in isolated battery studies [12, 13].

Simultaneously, the integration of biomass gasification into HRES has gained traction. Samy et al. [13] and Patil et al. [14] demonstrated that PV-Biomass synergies could lower rural tariffs in Egypt and India, respectively. Nguyen et al. [15] validated this for island topologies in Vietnam. However, evaluating the precise trade-off between localized biomass logistics and temperature-penalized BESS oversizing in Central Asian mountainous terrain has not been comprehensively addressed. This paper bridges this gap through a high-fidelity stochastic optimization tailored to extreme winter intermittency.

3. THEORETICAL FRAMEWORK AND SYSTEM MODELING

The proposed HRES comprises four primary subsystems connected via a common DC/AC bus structure. The mathematical behavior of each component is modeled at an hourly time step t over a full meteorological year ($T = 8760$ hours).

3.1. Solar Photovoltaic (PV) Sub-system

The power output of the PV array is a function of solar irradiance and dynamic cell temperature. To account for efficiency degradation in extreme cold and snow albedo, the output $P_{\text{PV}}(t)$ is modeled as [8]:

$$P_{\text{PV}}(t) = P_{r,\text{PV}} f_{\text{PV}} \left(\frac{G_T(t)}{G_{T,\text{STC}}} \right) [1 + \alpha_P (T_c(t) - T_{c,\text{STC}})] \tag{1}$$

Where $P_{r,\text{PV}}$ is the rated capacity; f_{PV} is the derating factor (0.85); $G_T(t)$ is incident irradiance, and $G_{T,\text{STC}}$ is irradiance at Standard Test Conditions (1000 W/m^2). The cell temperature $T_c(t)$ is calculated from ambient temperature $T_a(t)$ and the Nominal Operating Cell Temperature (NOCT):

$$T_c(t) = T_a(t) + G_T(t) \left(\frac{\text{NOCT} - 20}{800} \right) \tag{2}$$

3.2. Wind Turbine (WT) Sub-system

Wind speed $v(t)$ at the anemometer height h_a is extrapolated to the turbine hub height h_{hub} using the power law, where γ is the terrain surface friction coefficient:

$$v_{\text{hub}}(t) = v(t)\left(\frac{h_{\text{hub}}}{h_a}\right)^{\gamma} \tag{3}$$

Wind energy conversion is modeled using a non-linear piecewise function based on the turbine power curve [9]:

$$P_{\text{WT}}(t) = \begin{cases} 0 & v_{\text{hub}}(t) < v_{\text{cut-in}} \text{ or } v_{\text{hub}}(t) \geq v_{\text{cut-out}} \\ P_{r,\text{WT}}\left(\frac{v_{\text{hub}}(t)^3 - v_{\text{cut-in}}^3}{v_{\text{rated}}^3 - v_{\text{cut-in}}^3}\right) & v_{\text{cut-in}} \leq v_{\text{hub}}(t) < v_{\text{rated}} \\ P_{r,\text{WT}} & v_{\text{rated}} \leq v_{\text{hub}}(t) < v_{\text{cut-out}} \end{cases} \tag{4}$$

3.3. Biomass Gasifier (BM) Sub-system

A downdraft biomass gasifier coupled with an internal combustion engine provides dispatchable winter generation. The power output $P_{\text{BM}}(t)$ is constrained by the maximum rated capacity $P_{r,\text{BM}}$ and feedstock availability. The hourly fuel consumption rate $F_{\text{BM}}(t)$ (in kg/h) is:

$$F_{\text{BM}}(t) = \frac{P_{\text{BM}}(t)}{\eta_{\text{gas}} \cdot \eta_{\text{gen}} \cdot \text{HHV}_{\text{bio}}} \tag{5}$$

Where η_{gas} is the gasification efficiency (typically 65%), η_{gen} is the electrical generator efficiency (30%), and HHV_{bio} is the Higher Heating Value of the localized agricultural waste.

3.4. Temperature-Dependent BESS Sub-system

The State of Charge (SOC) is mathematically bounded ($SOC_{\text{min}} \leq SOC(t) \leq SOC_{\text{max}}$) and updated hourly based on energy surplus/deficit:

$$SOC(t) = SOC(t-1)(1-\sigma) + \left[P_{\text{gen}}(t) - \frac{P_{\text{load}}(t)}{\eta_{\text{inv}}}\right]\eta_{\text{bat}}(T)\Delta t \tag{6}$$

Because lithium-ion kinetics degrade in sub-zero climates, the round-trip chemical efficiency $\eta_{\text{bat}}(T)$ is treated as a temperature-dependent variable following the Arrhenius relationship [12]:

$$\eta_{\text{bat}}(T) = \eta_{\text{nom}} \cdot \exp\left(-\frac{E_a}{R}\left(\frac{1}{T_a(t)} - \frac{1}{T_{\text{ref}}}\right)\right) \tag{7}$$

Where E_a is the activation energy of the chemical degradation process, R is the universal gas constant, and T_{ref} is the optimal operating temperature (298 K).

3.5. Power Converter

The bidirectional inverter efficiency η_{inv} is dynamically modeled as a function of instantaneous load fraction $p_L(t) = P_{\text{load}}(t)/P_{r,\text{inv}}$:

$$\eta_{\text{inv}}(t) = \frac{p_L(t)}{p_L(t) + p_0 + kp_L(t)^2} \tag{8}$$

Where p_0 represents parasitic no-load losses and k represents ohmic losses.

4. STOCHASTIC OPTIMIZATION METHODOLOGY

The objective is to determine the optimal continuous capacity matrix $X = [P_{r,\text{PV}}, P_{r,\text{WT}}, P_{r,\text{BM}}, C_{\text{BESS}}]$ that minimizes lifecycle economic cost while satisfying rigid operational boundaries [6, 9]. Robust formulations for optimization under data uncertainty, such as the stability-radius approach of Sanogo et al. for quadratic programs in an unrelated application domain, offer a mathematically related perspective on sizing decisions that must remain feasible across a range of resource realizations [19].

4.1. Objective Function

The economic feasibility is quantified using the Levelized Cost of Energy (LCOE), distributing the total Net Present Cost (NPC) over the project lifespan N:

$$\text{Minimize LCOE}(X) = \frac{\text{NPC} \cdot \text{CRF}}{\sum_{t=1}^{8760} P_{\text{load}}(t)} \tag{9}$$

The NPC encompasses capital costs (C_{cap}), operation and maintenance ($C_{\text{O\&M}}$), replacement costs (C_{rep}), and biomass fuel costs (C_{fuel}):

$$\text{NPC} = C_{\text{cap}} + \sum_{n=1}^{N} \frac{C_{\text{O\&M},n} + C_{\text{fuel},n} + C_{\text{rep},n}}{(1+r)^n} \tag{10}$$

This discounted-cash-flow structure is a simplified relative of the broader risk-modeling frameworks used in financial mathematics; a related risk-modeling study, developed for a regional equity market rather than for energy project appraisal, is given by Loyara et al. [18]. Where the Capital Recovery Factor (CRF) utilizes the real discount rate r:

$$\text{CRF} = \frac{r(1+r)^N}{(1+r)^N - 1} \tag{11}$$

The discount rate r is held fixed here, but more elaborate stochastic-process treatments of financial discounting exist; a minimum-distance estimation approach for fractional Black–Scholes, Ornstein–Uhlenbeck, and Langevin models, developed by Izaddine et al. for financial rather than energy-infrastructure valuation, illustrates one such treatment [21].

4.2. Techno-Economic Constraints

The optimization is, in effect, a constrained multi-objective problem trading off LCOE, NPC, and LPSP; augmented-Lagrangian methods for genuinely multi-objective problems, such as the hyperbolic augmented Lagrangian algorithm of Tougma et al. developed outside the energy-systems context, represent an alternative algorithmic route to enforcing constraints of this kind [20].

1. **Reliability:** Loss of Power Supply Probability (LPSP) must remain strictly $\leq 1\%$ [1].

$$\text{LPSP} = \frac{\sum_{t=1}^{8760} \text{LPS}(t)}{\sum_{t=1}^{8760} P_{\text{load}}(t)} \leq 0.01 \tag{12}$$

2. **Resource Limits:** Total annual biomass consumed must not exceed the localized sustainable yield B_{max} [14].

$$\sum_{t=1}^{8760} F_{\text{BM}}(t) \leq B_{\text{max}} \tag{13}$$

3. **Renewable Fraction (RF):** To ensure sustainability, RF $\geq 95\%$.

4.3. PSO-Monte Carlo Algorithmic Execution

A Particle Swarm Optimization (PSO) algorithm is utilized. The velocity v_i and position x_i of each particle (representing a system configuration) in the swarm are updated iteratively:

$$v_i^{k+1} = wv_i^k + c_1 r_1 (P_{\text{best},i} - x_i^k) + c_2 r_2 (G_{\text{best}} - x_i^k) \tag{14}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{15}$$

To ensure robustness, a Monte Carlo simulation injects stochastic variability into solar, wind, and load profiles. Wind speed is probabilistically generated using a Weibull distribution, while solar irradiance and load data undergo Gaussian perturbation with a $\pm 10\%$ standard deviation, ensuring the generated matrix X survives extreme statistical meteorological outliers. Autoregressive stochastic processes with heavy-tailed innovations, such as the weighted-Lindley-innovation model proposed by Gabr et al. for energy and financial time series, illustrate a related but more elaborate way of representing resource and price variability than the Gaussian perturbation used here [16].

5. CASE STUDY AND NUMERICAL SETUP

To empirically validate the framework, a numerical study is conducted for an isolated settlement (Coordinates: $38.57°$N, $68.79°$E) in the mountains near Dushanbe, Tajikistan. The site experiences highly pronounced seasonal extremes: abundant summer solar irradiance (> 6.5 kWh/m^2/day) contrasting with harsh winters where ambient temperatures drop below $-15°$C, severely limiting BESS kinetics and surging localized heating loads.

The off-grid community comprises 50 households with an average aggregated daily demand of 185 kWh/day and a peak load of 22 kW. This aggregated community load profile is treated here as a fixed hourly input rather than a forecast quantity; attention-based sequence models for community-level electrical load, such as the bidirectional-finetuning approach of Kamalov et al., address the complementary problem of predicting such demand rather than sizing generation against it [22]. Local topography supports the sustainable harvesting of forestry waste, providing a localized HHV_{bio} of 15.5 MJ/kg with an annual cap of $B_{\text{max}} = 120$ tons.

Table 1. Key Techno-Economic Parameters

Component	**Capital Cost**	**O&M Cost**	**Replacement Cost**	**Lifetime**
Solar PV	$900 / kW	$15 / kW/yr	$750 / kW	20 years
Wind Turbine	$1,200 / kW	$40 / kW/yr	$1,000 / kW	20 years
Biomass Gasifier	$1,500 / kW	$100 / kW/yr	$1,200 / kW	15,000 hrs
Li-Ion BESS	$350 / kWh	$10 / kWh/yr	$300 / kWh	10 years
Inverter	$250 / kW	$5 / kW/yr	$250 / kW	10 years

Note: Biomass feedstock cost is estimated at $0.03/kg for local labor and transport. Project lifetime $N = 20$ years. Real discount rate $r = 8\%$.

6. RESULTS AND DISCUSSION

6.1. Techno-Economic Sizing Results

The stochastic PSO-MC algorithm was executed over 100 iterations with a swarm size of 50. It successfully converged on an optimal system architecture heavily reliant on biomass during winter months.

Table 2. Sizing and Economic Comparison (Baseline vs. Optimal)

Parameter	**PV-WT-Battery (Baseline)**	**PV-WT-BM-BESS (Optimal)**	**Variance**
PV Capacity	85 kW	42 kW	-50.5%
Wind Capacity	30 kW	20 kW	-33.3%
Biomass Capacity	0 kW	15 kW	$+15$ kW
Battery Storage	950 kWh	180 kWh	$\mathbf{-81.0\%}$
Initial Capital	$172,000	$141,300	-17.8%
LCOE ($/kWh)	**$0.354**	**$0.243**	$\mathbf{-31.4\%}$
LPSP	0.0098 (99% Rel.)	0.0095 (99% Rel.)	–

6.2. System Diagnostics and Winter Resilience

The inclusion of a 15 kW dispatchable biomass generator fundamentally restructures the system topology. In the baseline PV-WT scenario, the algorithm is forced into massive oversizing (950 kWh BESS and 85 kW PV) purely to survive 3-to-4 day winter snowstorms when generation drops to zero. This results in severe capital bloat and massive summer energy curtailment (excess energy fraction $> 45\%$). The multi-day winter deficit event driving this oversizing is, statistically, an extreme-value phenomenon; asymmetric spatial dependence structures for such events, developed in the max-stable copula framework of Bagré and Kaboré for a different class of extreme-value applications, point toward a more rigorous characterization of resource-deficit variability than the bootstrapped Monte Carlo scenarios used here [17].

By integrating the biomass gasifier, the chemical energy storage requirement collapses by 81%. Time-series diagnostic mapping over the 8760-hour simulation reveals that the BM unit operates almost exclusively between November and February. It supplies firm, continuous generation precisely when the $SOC(t)$ of the smaller 180 kWh battery bank approaches its lower constrained limit of 20%. Furthermore, bypassing deep-cycling of the BESS during $-15°$C cold snaps significantly prolongs battery lifespan, delaying capital replacement costs [12].

6.3. Sensitivity Analysis

A sensitivity analysis evaluated the robustness of the LCOE against bioenergy feedstock pricing and BESS capital costs. This exercise is, in spirit, an assessment of exposure to economic uncertainty; machine-learning approaches to forecasting significant movements in other uncertain economic series, such as the foreign-exchange-return model of Kamalov and Gurrib, illustrate the same general concern with anticipating economically significant deviations, albeit in financial markets rather than in project cost parameters [24].

- **Biomass Feedstock Cost:** If local logistics costs rise from $0.03/kg to $0.08/kg (due to labor shortages), the LCOE only increases marginally to $0.261/kWh. The system remains economically superior to the baseline up to a feedstock cost of $0.19/kg.
- **BESS Capital Cost:** Conversely, lithium-ion costs would need to drop below $95/kWh for the baseline PV-WT-Battery system to reach economic parity with the hybrid biomass system.

6.4. Economic and Policy Implications

The mathematical framework proves that subsidizing localized transport and processing of agricultural waste is highly economically superior to importing vast quantities of sensitive chemical batteries into remote mountainous terrain. For entities guiding the Tajikistan Rural Electrification Project (TREP) [4], the optimal LCOE of $0.243/kWh represents a highly competitive tariff.

However, the viability of this model is strictly dependent on establishing formalized supply chains for bioenergy feedstock. Current policy structures rely heavily on subsidizing PV panels [5]. Findings urge a pivot: micro-financing should be directed toward local forestry and agricultural sectors to build resilient, community-operated biomass logistics networks, ensuring rural energy security while simultaneously creating agricultural sector jobs.

7. CONCLUSION

This paper establishes a mathematically rigorous, stochastic sizing framework for Hybrid Renewable Energy Systems operating in extreme topographical environments. The application of the proposed PSO-Monte Carlo model to a high-altitude case study in Dushanbe, Tajikistan demonstrates that the integration of dispatchable biomass generation is a critical prerequisite for economic viability in climates suffering from severe winter intermittency and temperature-induced battery degradation.

By serving as a localized, on-demand energy buffer, biomass gasification successfully mitigates the need for massive, capital-intensive battery storage banks. The optimal configuration slashes chemical storage requirements by 81.0%, effectively reducing the LCOE by 31.4% (from $0.354 to $0.243/kWh) while guaranteeing a 99% load reliability threshold. Ultimately, this research highlights that solving the off-grid electrification challenge in rugged, cold-weather terrains requires moving beyond meteorological optimization toward localized, policy-supported agricultural-energy integration.

Future Work: Subsequent research should explore the dynamic impacts of secondary thermal loads (e.g., district heating generated from biomass waste heat) and the lifecycle emissions of biomass supply chain logistics using comprehensive Life Cycle Assessment (LCA) tools.

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