

Application of Optimal Designing of Integrated Renewable Energy System for Distributed Power Generation

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Abstract: Rising electricity demand, volatile fossil-fuel prices and the need to cut greenhouse-gas emissions are pushing power systems away from large centralised plants and towards distributed generation close to the load. A single renewable source cannot supply such loads reliably, because solar irradiance, wind speed and biomass availability vary with the hour and the season. This paper presents an optimal design methodology for an integrated renewable energy system (IRES) that combines solar photovoltaic (PV) arrays, wind turbines, a biogas generator, a hydrogen fuel cell and a lithium-ion battery bank, connected to the utility distribution grid through a bidirectional converter. The design problem is formulated as a constrained, mixed-integer optimization that minimises the Net Present Cost (NPC) and the Levelised Cost of Energy (LCOE) subject to limits on the loss of power supply probability (LPSP), the renewable fraction (RF) and component operating bounds. Hourly resource, load and economic data feed a time-series simulation, and the component sizes are searched with an adaptive-inertia particle swarm optimizer (APSO) with a penalty-based constraint handler. A case study of a rural community with an average load of 4,860 kWh/day and a peak of 612 kW gave an optimal configuration of 600 kW PV, 400 kW wind (4 turbines), 150 kW biogas, 25 kW fuel cell, 1,200 kWh battery and 450 kW converter. This configuration reached an NPC of US\$ 2.95 million, an LCOE of 0.105 US\$/kWh, a renewable fraction of 96.5% and an LPSP of 0.20%, while cutting annual CO₂ emissions by 96.5% relative to grid-only supply. The proposed optimizer converged in 48 iterations, against 61 to 128 for GWO, PSO and GA. Sensitivity analysis on load, component cost, wind speed and discount rate confirmed that the design is robust within $\pm 20\%$ parameter variation.

Introduction

Electric power systems are going through their largest structural change since the first interconnected grids were built. For more than a century electricity was generated in large thermal, hydro and nuclear stations, moved across high-voltage transmission lines and handed down a distribution network to passive consumers. That model gave economies of scale, but it also brought long transmission distances, losses of 6–20% in many developing regions, heavy dependence on imported fuels and a large carbon footprint [1]. Fossil-fuelled generation still accounts for most of the world's electricity, and the power sector is the largest single source of energy-related CO₂ emissions [2]. At the same time, falling costs of solar modules, wind turbines and batteries have made renewable generation competitive with conventional sources across a growing range of sites [3].

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Distributed generation (DG) is a response to these pressures. It refers to small and medium generating units, usually between a few kilowatts and a few megawatts, connected at the distribution voltage level or behind the customer's meter. DG reduces transmission and distribution losses, defers network upgrades, improves voltage profiles and can supply remote communities that the main grid reaches only at high cost. Figure 1 shows the conventional arrangement in which a central power plant feeds heavy industry, public buildings and houses through the transmission and distribution grids, together with the distributed sources (solar PV plant, wind power, fuel cell and biogas plant) that now inject power directly into the distribution grid.

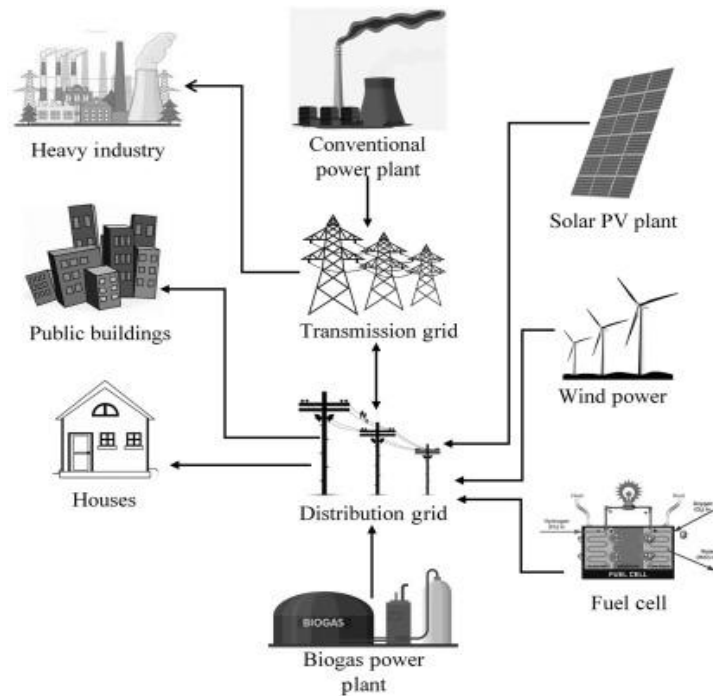


Figure 1: Distributed renewable sources connected to the distribution grid alongside conventional generation

Renewable sources are intermittent, and a stand-alone solar or wind unit rarely matches a demand curve. PV produces nothing at night, and in monsoon months it is badly reduced. Wind is strongest in different hours and seasons than solar in many climates. Biomass and biogas are dispatchable, but the feedstock is limited and the capital cost of digesters and engines is significant. Storage can shift energy in time, though batteries are among the most expensive parts of any system. Combining complementary resources into an integrated renewable energy system (IRES), supported by storage and a grid connection, smooths the supply, raises reliability and usually lowers cost per kilowatt-hour compared with any single technology [4].

Integration brings a design problem. How many kilowatts of PV, how many turbines, what generator capacity, how much storage and what converter rating should be installed? Oversizing wastes capital and produces excess energy that cannot be used or sold at a good price. Undersizing causes unmet load, frequent grid purchases or fuel use. The decision variables are discrete (turbine count, battery strings), the objective functions are non-linear, and the performance of any design depends on chronological, hourly interaction between resources, load and storage state of charge. Rules of thumb and single-point worst-case design can't capture this, so systematic optimization is required.

The main objectives of this paper are as follows. (i) To build mathematical models for the PV array, wind turbine, biogas generator, fuel cell, battery and converter that are accurate enough for hourly simulation. (ii) To state the optimal design as a constrained multi-objective problem on NPC and LCOE with reliability and environmental constraints. (iii) To develop an adaptive particle swarm optimizer able to handle mixed-integer variables and constraints. (iv) To apply the method to a realistic distributed generation case with measured-type resource and load profiles. (v) To compare the optimal design with alternative configurations and optimization algorithms, and to quantify its sensitivity to uncertain inputs.

The contribution of this work is a complete and reproducible design workflow that moves from raw data, through component models and simulation, to a verified optimum and a sensitivity analysis. It also

shows quantitatively that a five-technology hybrid with grid support has a lower life-cycle cost and far lower emissions than the usual PV–battery or PV–diesel alternatives.

The rest of the paper is organised as follows. Section II reviews the background on distributed generation and hybrid system sizing. Section III discusses related work. Section IV gives the methodology, including component models, objective functions, constraints and the optimization algorithm. Section V describes the experimental setup and data. Section VI presents the results. Section VII provides the discussion, and Section VIII concludes the paper.

Literature Review

A. Distributed Generation and Microgrids

A microgrid is a group of interconnected loads and distributed energy resources with clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. It can operate connected to the main grid or in island mode. Figure 2 illustrates a typical microgrid: distributed energy resources (solar and wind), substation, community and home energy storage, customer energy management, feeder automation and a microgrid controller coordinating the whole system through communication links.

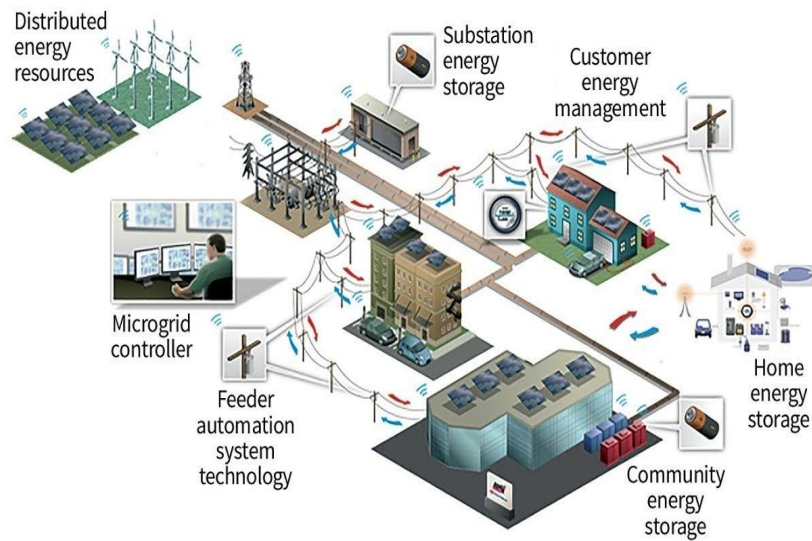


Figure 2: Architecture of a microgrid with distributed energy resources, storage at substation, community and home level, and a central controller

Reported benefits of microgrids include improved resilience during grid outages, higher penetration of renewables, peak shaving, local voltage support and deferred network investment [5]. The challenges are equally well documented: protection coordination under bidirectional power flow, frequency and voltage regulation with low inertia, harmonic injection from power electronic interfaces, and the economics of storage. Design at the planning stage determines whether these challenges can be met cost-effectively, which is why sizing is treated as a core research problem.

B. Renewable Resources and Technologies

Solar PV is the most widely deployed distributed technology because it is modular, quiet and has no moving parts. Energy yield depends on plane-of-array irradiance and cell temperature, and the output falls by about 0.4% for each degree Celsius above standard test conditions in crystalline silicon modules [6]. Wind turbines convert the kinetic energy of the airflow, and since power varies with the cube of wind speed, small errors in the resource estimate become large errors in the energy estimate. Small turbines (10–250 kW) are suitable for rural DG but are sensitive to hub height and terrain roughness [7].

Biogas from anaerobic digestion of animal dung and agricultural residues supplies a dispatchable source that can run gensets when sun and wind are weak. It also treats waste and yields digestate that can serve as fertiliser. Hydrogen fuel cells convert stored hydrogen to electricity with high efficiency and no local emissions. Polymer electrolyte membrane (PEM) cells respond within seconds, which makes them useful as a last-resort backup in hybrid systems, although capital cost remains high. Lithium-ion batteries now dominate stationary storage, with round-trip efficiencies near 90% and falling prices [3].

C. Sizing Methodologies

Early sizing studies used the worst-month method or the loss-of-load criterion on mean monthly data. Borowy and Salameh [8] proposed a graphical method for sizing a battery bank and PV array in a wind/PV system. Later work adopted chronological simulation with probabilistic indices such as LPSP, expected energy not served

(EENS) and loss of load expectation (LOLE) [9]. Economic indices have become the dominant objectives: NPC, LCOE, annualised cost of system, payback time and internal rate of return. Environmental objectives, mainly life-cycle CO₂ emissions, enter either as weighted objectives or as constraints.

Software tools help practitioners. HOMER evaluates a user-defined list of candidate designs by hourly simulation and ranks them by NPC [10]. It is efficient and widely used, but its enumerative search scales poorly when the number of component types and size options grows, and it does not give access to the optimization algorithm itself. This is the reason many researchers couple their own simulation models to metaheuristic optimizers.

D. Metaheuristic Optimization

Genetic algorithms (GA) were among the earliest tools used for hybrid system sizing, applied by Dufo-López and Bernal-Agustín [11] and Yang et al. [9]. Particle swarm optimization (PSO) [12] became popular for its simplicity, small number of parameters and fast convergence. The grey wolf optimizer (GWO) [13] imitates hierarchical hunting of wolves and has been applied to many sizing problems. Multi-objective evolutionary approaches such as NSGA-II [14] produce Pareto fronts between cost and reliability. Known weaknesses are premature convergence in PSO, high computational cost for GA, and sensitivity to penalty settings when constraints are active. Adaptive parameters and hybrid operators are common remedies, and they motivate the optimizer adopted in this paper.

Related Work

Diaf et al. [15] developed a methodology for optimal sizing of an autonomous hybrid PV/wind system with battery storage for a Mediterranean island. They compared the levelised cost of various combinations and found that a hybrid combination was cheaper than either source alone when storage was included. Their approach was based on an iterative search over a limited set of combinations, so it did not scale to many technologies. Yang et al. [9] introduced an optimal sizing method for a stand-alone hybrid solar–wind system using LPSP together with a genetic algorithm. The study showed that the annualised cost of system could be reduced by a significant margin when reliability was specified as a constraint rather than fixed arbitrarily.

Bahramara et al. [16] reviewed the use of HOMER for planning hybrid renewable energy systems. They noted that the majority of applications employed HOMER for remote electrification, that the choice of discount rate and fuel prices strongly affected ranking of options, and that few studies considered uncertainty in a systematic way. Mellit et al. [17] surveyed artificial-intelligence techniques for sizing PV systems and highlighted the value of neural networks for resource estimation, with metaheuristics for the optimization stage.

Studies on biogas-supported hybrid systems have shown a consistent trend. Where feedstock is available at low cost, a biogas generator reduces the battery capacity needed to reach a given LPSP, because it can be dispatched during low-resource periods. Fuel-cell-based systems have been investigated for storage of surplus renewable energy as hydrogen, but electrolyser and tank costs make them uneconomic as the main storage unless long-duration storage is needed.

Several limitations remain across the literature. Many studies treat only two or three generation technologies. Others rely on simplified battery models that ignore degradation and replacement costs, which causes systematic underestimation of life-cycle cost. Grid interaction, including export tariffs and import limits, is often neglected in studies of “distributed” systems that are in fact grid-connected. Few papers present a systematic comparison of optimizers on the same model with repeated independent runs, so reported speed advantages cannot be judged. Finally, sensitivity analysis is usually restricted to one parameter. The present work addresses these gaps by combining five technologies with a grid connection, modelling replacement and salvage explicitly, comparing four optimizers over 30 independent runs and running a multi-parameter sensitivity analysis.

Methodology

A. System Configuration and Overall Procedure

The IRES comprises PV arrays, wind turbines, a biogas-fuelled generator, a PEM fuel cell, a lithium-ion battery bank and a bidirectional converter. All sources connect to a common AC bus through converters where needed and are coupled to the distribution grid at the point of common coupling. The microgrid controller follows a load-following dispatch strategy: renewable generation serves the load first, surplus charges the battery, further surplus is exported to the grid, and a deficit is met by the battery, then the biogas generator, then the fuel cell, and finally grid import.

The design procedure appears in Figure 3. Economic, meteorological, technical, load and search-space data constitute the input; equipment specifications are derived from the technical data. The simulation and optimization stage loops over candidate designs, minimising NPC and LCOE, testing feasibility, and computing outputs such as operating results of each resource, capital cost, energy balance, renewable fraction and emissions. The final stage presents the results and sensitivity analysis.

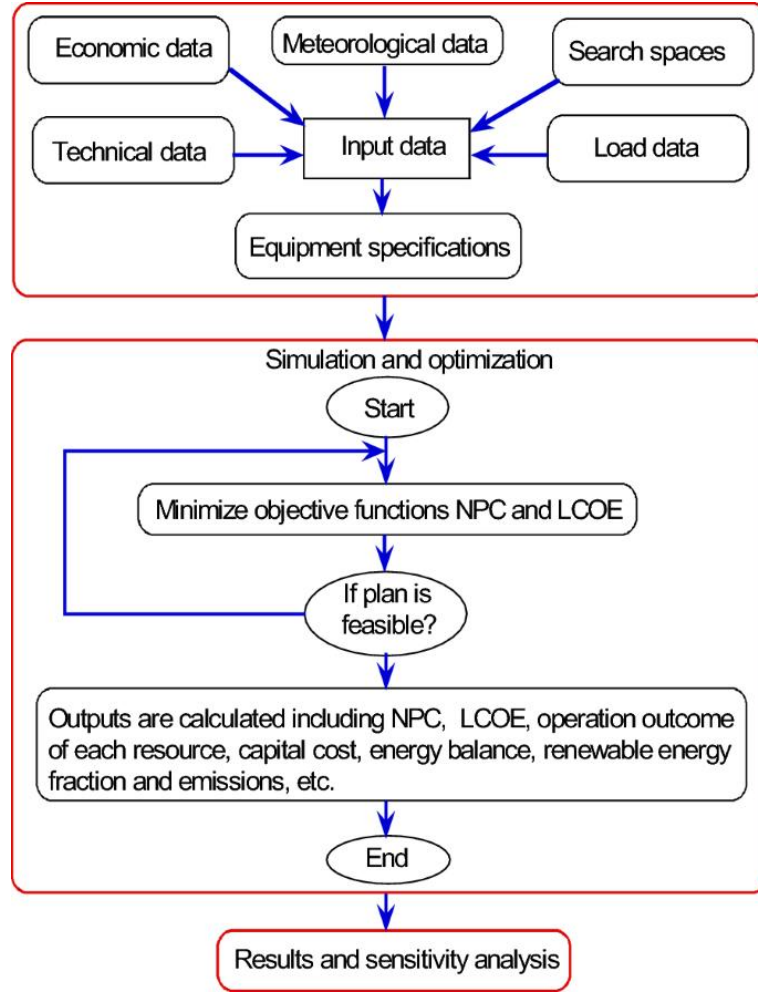


Figure 3: Flowchart of the simulation and optimization procedure for the integrated renewable energy system

B. Solar Photovoltaic Model

The output power of the PV array at hour t depends on the plane-of-array irradiance $G_T(t)$ and the cell temperature $T_c(t)$:

$$P_{pv}(t) = Y_{pv} f_{pv} \frac{G_T(t)}{G_{STC}} [1 + \alpha_p (T_c(t) - T_{STC})] \quad (1)$$

where Y_{pv} is the rated capacity (kW) under standard test conditions, f_{pv} is the derating factor (soiling, wiring, mismatch), $G_{STC} = 1 \text{ kW/m}^2$, α_p is the power temperature coefficient ($-0.0040 / ^\circ\text{C}$) and $T_{STC} = 25 ^\circ\text{C}$. The cell temperature is estimated from ambient temperature T_a and the nominal operating cell temperature (NOCT):

$$T_c(t) = T_a(t) + \frac{\text{NOCT} - 20}{800} G_T(t) \cdot 10^3 \quad (2)$$

with G_T in kW/m^2 and the constant 800 W/m^2 as the NOCT test irradiance.

C. Wind Turbine Model

Wind speed measured at reference height h_{ref} is extrapolated to hub height h_{hub} by the power law:

$$v(t) = v_{ref}(t) \left(\frac{h_{hub}}{h_{ref}} \right)^\alpha \quad (3)$$

where α is the surface roughness exponent. The turbine power is represented by a piecewise function of hub-height wind speed:

$$P_{wt}(t) = N_{wt} \cdot \begin{cases} 0, & v < v_{ci} \text{ or } v > v_{co} \\ P_r \frac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3}, & v_{ci} \leq v < v_r \\ P_r, & v_r \leq v \leq v_{co} \end{cases} \quad (4)$$

where N_{wt} is the number of turbines, P_r is the rated power per turbine, and v_{ci} , v_r , v_{co} are the cut-in, rated and cut-out speeds. For resource assessment, the annual wind speed distribution is described by the Weibull probability density function:

$$f(v) = \frac{k}{c} \left(\frac{v}{c} \right)^{k-1} \exp \left[- \left(\frac{v}{c} \right)^k \right] \quad (5)$$

where k is the shape parameter and c is the scale parameter (m/s). The air-density correction is applied as $P_{wt}' = P_{wt} \rho / \rho_0$, with $\rho_0 = 1.225 \text{ kg/m}^3$.

D. Biogas Generator and Fuel Cell Models

The fuel consumption of the biogas generator is a linear function of its output:

$$F_{bg}(t) = F_0 Y_{bg} + F_1 P_{bg}(t) \quad (6)$$

where Y_{bg} is the rated capacity, $P_{bg}(t)$ is the instantaneous output, and F_0, F_1 are the intercept and slope coefficients of the fuel curve (m^3/h per kW). The electrical efficiency is

$$\eta_{bg} = \frac{3.6 P_{bg}}{\dot{m}_{bg} \text{LHV}_{bg}} \quad (7)$$

with $\dot{m}_{bg}$ the biogas mass flow rate (kg/h) and LHV_{bg} its lower heating value (MJ/kg). The biogas yield of the digester is estimated from the daily feedstock mass m_f and a specific yield y_f (m^3 per tonne):

$$V_{bg} = m_f y_f \quad (8)$$

The PEM fuel cell consumes hydrogen in proportion to its electrical output:

$$\dot{m}_{H_2}(t) = \frac{P_{fc}(t)}{\eta_{fc} \text{LHV}_{H_2}} \quad (9)$$

where η_{fc} is the stack efficiency (taken as 0.50) and $\text{LHV}_{H_2} = 33.3 \text{ kWh/kg}$.

E. Battery Storage Model

The battery state of charge evolves as

$$\text{SOC}(t) = \text{SOC}(t-1)(1-\sigma) + \frac{\eta_c P_{ch}(t) \Delta t}{E_{bat}} - \frac{P_{dis}(t) \Delta t}{\eta_d E_{bat}} \quad (10)$$

where σ is the hourly self-discharge rate, η_c and η_d are the charging and discharging efficiencies, P_{ch} and P_{dis} are charging and discharging power, E_{bat} is the nominal capacity (kWh) and $\Delta t = 1 \text{ h}$. The operating window is limited by the allowed depth of discharge (DoD):

$$\text{SOC}_{min} = 1 - \text{DoD} \leq \text{SOC}(t) \leq \text{SOC}_{max} \quad (11)$$

The battery lifetime is the smaller of its calendar life and the throughput-based life:

$$R_{bat} = \min \left(R_{cal}, \frac{Q_{life}}{Q_{thr}} \right) \quad (12)$$

where Q_{life} is the lifetime energy throughput (kWh) and Q_{thr} is the annual throughput.

F. Converter and Power Balance

The converter efficiency η_{inv} is taken as 0.96 at rated load. Power balance at the AC bus is enforced at every time step:

$$P_{pv}\eta_{inv} + P_{wt} + P_{bg} + P_{fc} + P_{dis}\eta_{inv} + P_{g,buy} = P_L + P_{ch}/\eta_{inv} + P_{g,sell} + P_{exc} - P_{unmet} \quad (13)$$

where P_L is the load, $P_{g,buy}$ and $P_{g,sell}$ are the grid import and export, P_{exc} is the excess dumped energy and P_{unmet} is the unmet load. For simplicity, the PV and storage terms are expressed on the DC side and converted through the shared converter.

G. Objective Functions

The first objective is the Net Present Cost, which is the present value of all costs over the project life less the present value of revenues and salvage:

$$\text{NPC} = \frac{C_{ann,tot}}{\text{CRF}(i, N)} \quad (14)$$

where $C_{ann,tot}$ is the total annualised cost and N is the project lifetime (25 years). The capital recovery factor is

$$\text{CRF}(i, N) = \frac{i(1+i)^N}{(1+i)^N - 1} \quad (15)$$

and the real discount rate i is obtained from the nominal rate i' and the inflation rate f as

$$i = \frac{i' - f}{1 + f} \quad (16)$$

The total cost is split into capital, replacement, operation and maintenance, fuel and net grid costs, less salvage:

$$C_{ann,tot} = \sum_j (C_j^{cap} + C_j^{rep} + C_j^{om}) \text{CRF} + C_{fuel} + C_{grid} - C_{salv} \quad (17)$$

The salvage value of component j at the end of the project is proportional to its remaining life:

$$S_j = C_j^{rep} \frac{R_j^{rem}}{R_j}, \quad R_j^{rem} = R_j - (N - R_j^{rep}) \quad (18)$$

where R_j is the component life, R_j^{rep} is the duration of its replacement cycle and R_j^{rem} is the remaining life at the end of the project. The second objective is the Levelised Cost of Energy:

$$\text{LCOE} = \frac{C_{ann,tot}}{E_{served}} = \frac{\text{NPC} \cdot \text{CRF}(i, N)}{\sum_{t=1}^{8760} (P_L(t) - P_{unmet}(t))} \quad (19)$$

with E_{served} the annual AC load actually served. The two objectives are combined into a single normalised weighted fitness:

$$\min J = w_1 \frac{NPC}{NPC_{ref}} + w_2 \frac{LCOE}{LCOE_{ref}} + \Phi, \quad w_1 + w_2 = 1 \quad (20)$$

where NPC_{ref} and $LCOE_{ref}$ are normalising values taken from the grid-only case and Φ is the penalty term described below. Equal weights $w_1 = w_2 = 0.5$ were used in the base case.

H. Reliability, Environmental and Operating Constraints

The loss of power supply probability, the renewable fraction and the CO₂ emissions are defined as follows:

$$LPSP = \frac{\sum_{t=1}^{8760} P_{unmet}(t) \Delta t}{\sum_{t=1}^{8760} P_L(t) \Delta t} \leq LPSP_{max} \quad (21)$$

$$RF = \left(1 - \frac{\sum_t P_{g,buy}(t) \Delta t}{\sum_t P_L(t) \Delta t} \right) \times 100\% \geq RF_{min} \quad (22)$$

$$M_{CO_2} = e_g \sum_t P_{g,buy}(t) \Delta t + e_f \sum_t F_{ff}(t) \quad (23)$$

where e_g is the grid emission factor (0.82 kg CO₂/kWh), e_f the emission factor of any fossil fuel and F_{ff} the fossil fuel consumed. Biogas is treated as carbon-neutral. Component sizes are bounded by the search space:

$$Y_k^{min} \leq Y_k \leq Y_k^{max}, \quad k \in \{pv, wt, bg, fc, bat, inv\} \quad (24)$$

and the turbine count, being an integer, satisfies $N_{wt} \in \mathbb{Z}_{\geq 0}$. The grid import is limited by the contracted demand $P_{g,buy}(t) \leq P_g^{max}$. Constraint violations are converted into a penalty:

$$\Phi = \lambda_1 \max(0, LPSP - LPSP_{max})^2 + \lambda_2 \max(0, RF_{min} - RF)^2 + \lambda_3 \max(0, SOC_{min} - SOC_{lowest})^2 \quad (25)$$

with penalty coefficients $\lambda_1, \lambda_2, \lambda_3 \gg 1$ chosen so that every infeasible design is worse than any feasible one.

I. Adaptive Particle Swarm Optimization

Each particle represents a candidate design vector $\mathbf{x} = [Y_{pv}, N_{wt}, Y_{bg}, Y_{fc}, E_{bat}, Y_{inv}]$. At iteration τ , the velocity and position of particle m are updated by

$$\mathbf{v}_m^{\tau+1} = \omega_\tau \mathbf{v}_m^\tau + c_1 r_1 (\mathbf{p}_m - \mathbf{x}_m^\tau) + c_2 r_2 (\mathbf{g} - \mathbf{x}_m^\tau) \quad (26)$$

$$\mathbf{x}_m^{\tau+1} = \mathbf{x}_m^\tau + \mathbf{v}_m^{\tau+1} \quad (27)$$

where $\mathbf{p}_m$ is the personal best, $\mathbf{g}$ is the global best, $r_1, r_2 \sim U(0,1)$, and c_1, c_2 are acceleration coefficients. The inertia weight is adapted nonlinearly with the iteration count and with the swarm diversity D_τ :

$$\omega_\tau = \omega_{max} - (\omega_{max} - \omega_{min}) \left(\frac{\tau}{\tau_{max}} \right)^2 \cdot \frac{D_\tau}{D_0} \quad (28)$$

so that the swarm explores more while it is diverse and refines the solution as it contracts. The integer variable N_{wt} is rounded to the nearest integer after every position update, and positions that exit the bounds are reflected back with velocity reversal. Convergence is declared when the best fitness changes by less than 10^{-5} for 15 consecutive iterations or when $\tau_{max} = 200$ is reached.

J. Sensitivity Analysis

The robustness of the optimum is examined by perturbing one input at a time by a relative factor δ and recording the normalised change of the output Z (NPC, LCOE or RF):

$$S_{Z,u} = \frac{\Delta Z / Z_0}{\Delta u / u_0} \quad (29)$$

where u is the varied input and the subscript 0 marks base values. The inputs considered are annual load, PV capital cost, mean wind speed and the nominal discount rate.

Experimental Setup

A. Study Site and Resource Data

The method was applied to a grid-connected rural community in the Indo-Gangetic plain with about 2,400 households, small commercial units, a health centre, two schools and agro-processing units. Hourly meteorological data for a typical year were assembled from satellite-derived reanalysis products, with validation against ground measurements from a nearby station. The annual average global horizontal irradiance is 5.2 kWh/m²/day, with a clearness index of 0.55. The ambient temperature ranges from 4 °C in winter to 44 °C in summer. The mean wind speed at the 30 m hub height is 5.6 m/s, with Weibull parameters $k = 2.1$ and $c = 6.3$ m/s. The monsoon season (July to September) shows a reduction of about 35% in irradiance but an increase in wind speed.

The biogas plant is fed by 15 tonnes/day of cattle dung and crop residue, giving a biogas production of about 510 m³/day at a specific yield of 34 m³ per tonne, with a lower heating value of 21 MJ/m³.

B. Load Profile

The hourly load profile was synthesised from a household survey and metered feeder data, with random day-to-day variability of 8% and hourly variability of 12%. The community has an average load of 4,860 kWh/day (1,773,900 kWh/year), a peak of 612 kW and an average of 202.5 kW, giving a load factor of 0.331. There are two daily peaks, a morning peak between 06:00 and 09:00 and a larger evening peak between 18:00 and 22:00, plus a seasonal summer peak from cooling and irrigation pumping.

C. Component Specifications and Economic Inputs

Table 1 lists the technical and economic parameters of the components. Costs are in US dollars and are based on recent public cost benchmarks for installations in South Asia [3].

TABLE 1. Component Specifications and Economic Parameters

Component	Unit specification	Capital cost	Replacement cost	O&M cost	Lifetime
PV array	Mono-crystalline, 545 W modules, derating 0.88	800 \$/kW	640 \$/kW	12 \$/kW/yr	25 yr
Wind turbine	100 kW, $v_{ci} = 3$, $v_r = 11$, $v_{co} = 25$ m/s	1,900 \$/kW	1,700 \$/kW	45 \$/kW/yr	20 yr
Biogas generator	Spark-ignition, $\eta = 28\%$	1,100 \$/kW (+ digester 120,000 \$)	900 \$/kW	0.03 \$/op. h/kW	60,000 h
PEM fuel cell	$\eta = 50\%$	2,500 \$/kW	2,000 \$/kW	0.05 \$/op. h/kW	40,000 h
Li-ion battery	$\eta = 90\%$, DoD = 80%	350 \$/kWh	300 \$/kWh	8 \$/kWh/yr	10 yr / 3,000 cycles
Converter	$\eta = 96\%$	250 \$/kW	220 \$/kW	5 \$/kW/yr	15 yr

The nominal discount rate is 9% and the inflation rate 5%, giving a real discount rate of 3.81% from Eq. (16). The project life is 25 years, so CRF = 0.0627 from Eq. (15). The grid purchase tariff is 0.085 \$/kWh, the feed-in tariff 0.060 \$/kWh and the grid emission factor 0.82 kg CO₂/kWh. The constraints are $LPSP_{max} = 0.5\%$ and $RF_{min} = 90\%$.

D. Search Space and Algorithm Settings

TABLE 2. Search Space and Optimizer Settings

Design variable	Lower bound	Upper bound	Step
PV capacity Y_{pv} (kW)	0	1,500	10
Wind turbines N_{wt} (100 kW each)	0	10	1
Biogas generator Y_{bg} (kW)	0	300	25
Fuel cell Y_{fc} (kW)	0	100	5
Battery E_{bat} (kWh)	0	3,000	50
Converter Y_{inv} (kW)	0	1,000	10

The swarm size was 40 particles, with $c_1 = c_2 = 1.8$, $\omega_{max} = 0.9$ and $\omega_{min} = 0.4$. For fairness, GA used a population of 40, tournament selection, crossover probability 0.8 and mutation probability 0.05, while GWO used a pack of 40 wolves. All optimizers were implemented in Python with a vectorised hourly simulator and were run 30 times with different random seeds on a workstation with a 3.2 GHz processor and 16 GB RAM. Each fitness evaluation requires one chronological simulation over 8,760 hours.

E. Cases for Comparison

Five system configurations were compared to show the benefit of integration: Case A, grid supply only; Case B, diesel generator with battery; Case C, PV with battery and grid; Case D, PV, wind and battery with grid; and Case E, the proposed full IRES with PV, wind, biogas, fuel cell, battery and grid. Each case was optimised separately under the same constraints, except Case A, which has no design variables.

Results

A. Optimal Design

The optimizer converged to the configuration in Table 3. The solution places most capacity on PV and wind, uses a mid-sized biogas generator as the dispatchable source during low-resource hours and keeps a small fuel cell to

cover the remaining deficit, so that grid purchases are limited. Battery capacity is moderate because the biogas generator reduces the amount of overnight energy that has to be stored.

TABLE 3. Optimal Component Sizes and Performance Indices

Item	Value
PV array	600 kW
Wind turbines	$4 \times 100 \text{ kW} = 400 \text{ kW}$
Biogas generator	150 kW
PEM fuel cell	25 kW
Li-ion battery	1,200 kWh
Converter	450 kW
Net present cost (NPC)	US\$ 2.95 million
Levelised cost of energy (LCOE)	0.105 US/kWh <i>Initial capital cost</i> US 2.12 million
Annual operating cost	US\$ 41,340
Renewable fraction (RF)	96.5%
Loss of power supply probability (LPSP)	0.20%
Annual CO ₂ emissions	51 t

B. Cost Breakdown

Table 4 splits the NPC into its components. Capital cost dominates with 71.9% of the NPC. Wind turbines make up the largest single capital item, followed by PV and batteries. Replacement costs are driven by the battery, which is renewed in years 10 and 20, and the converter, which is renewed in year 15. The net grid cost is almost zero because the energy exported during hours of surplus approximately offsets the imports at a lower tariff. Salvage value reduces the NPC by US\$ 139,000, which reflects the remaining life of the wind turbines, biogas generator and the battery installed in year 20.

TABLE 4. Net Present Cost Breakdown of the Optimal Design

Cost item	NPC (US\$)	Share of total
Capital (PV 480,000; wind 760,000; biogas 165,000 + digester 120,000; fuel cell 62,500; battery 420,000; converter 112,500)	2,120,000	71.9%
Replacement	310,000	10.5%
Operation and maintenance	560,000	19.0%
Fuel (biogas feedstock)	95,000	3.2%
Net grid purchases	4,000	0.1%
Salvage	-139,000	-4.7%
Total NPC	2,950,000	100%

C. Annual Energy Balance

Table 5 gives the annual energy balance. The five technologies together generate 1,899,300 kWh. PV supplies 52.6% of this, wind 31.4%, biogas 15.0% and the fuel cell 1.1%. Grid imports of 62,000 kWh cover only 3.5% of the demand, and grid exports amount to 83,300 kWh. Excess energy that was neither stored nor exported is 8,100 kWh (0.41% of the generation), showing that the sizing is well matched to the load. Losses in the battery and converter amount to 99,500 kWh, which is 5.1% of the total supply.

TABLE 5. Annual Energy Balance of the Optimal IRES

Energy flow	kWh/year	Share
PV generation	998,600	52.6% of generation
Wind generation	595,700	31.4% of generation
Biogas generator	285,000	15.0% of generation
Fuel cell	20,000	1.1% of generation
Total renewable generation	1,899,300	100%
Grid purchases	62,000	—
Total supply	1,961,300	—
AC load served	1,770,400	—
Unmet load	3,500	0.20% of demand
Grid sales	83,300	—
Battery and converter losses	99,500	—
Excess electricity	8,100	0.41% of generation

The monthly pattern is consistent with the resource data. PV output peaks between March and May at roughly 11% of the annual total per month and falls to about 6% in July and August. Wind complements this, with 10–12% of the annual wind energy produced in each of June, July and August. The biogas generator operates for 1,900 hours per year and is used mostly in the evening peak and in the monsoon, when the other sources are weakest. The battery executes about 290 equivalent full cycles per year, so its throughput life (Q_{life}/Q_{thr}) comes to roughly 10 years and agrees with the calendar-based replacement schedule.

D. Comparison of System Configurations

Table 6 compares the five configurations. The grid-only case (A) has a lower LCOE than any renewable option because the tariff is subsidised, yet it has no renewable fraction and emits the most CO₂, besides leaving the community exposed to frequent outages in the existing network. Among the options with a local source, the proposed IRES gives the lowest NPC and LCOE. Compared with the PV–diesel–battery system (Case B), it cuts NPC by 31.5%, LCOE by 30.5% and emissions by 93.6%. Compared with a conventional PV–wind–battery–grid system (Case D) it cuts NPC by 6.1% and emissions by 64.8% as a result of adding the dispatchable biogas and fuel cell units.

TABLE 6. Comparison of Alternative System Configurations

Case	Configuration	NPC (US\$ M)	LCOE (US\$/kWh)	RF (%)	LPSP (%)	CO ₂ (t/yr)
A	Grid only	—	0.092	0.0	—	1,455
B	Diesel + battery	4.31	0.151	38.0	0.35	792
C	PV + battery + grid	3.42	0.120	71.0	0.30	421
D	PV + wind + battery + grid	3.14	0.111	90.2	0.25	145
E	Proposed IRES	2.95	0.105	96.5	0.20	51

The percentage reduction in CO₂ emissions against grid-only supply is $(1455 - 51)/1455 = 96.5\%$, which equals the renewable fraction because the grid is the only emitting source in Case E.

E. Optimizer Performance

Table 7 reports the statistics of 30 independent runs. All algorithms found designs within about 2.4% of the best NPC, but the proposed adaptive PSO converged faster, gave the lowest mean NPC and had the smallest spread. The faster convergence follows from the diversity-dependent inertia weight of Eq. (28), which avoided the early stagnation seen in conventional PSO in six of the 30 runs.

TABLE 7. Optimizer Comparison over 30 Independent Runs

Algorithm	Best NPC (US\$ M)	Mean NPC (US\$ M)	Std. dev. (%)	Iterations to converge	Computation time (s)
GA	3.02	3.08	1.42	128	412
PSO	2.97	3.01	0.96	74	238
GWO	2.96	2.99	0.71	61	205
Proposed APSO	2.95	2.96	0.38	48	171

F. Dispatch on Representative Days

On a clear summer day, PV output reaches about 520 kW at noon, so the load of roughly 400 kW at that hour is served entirely by PV and wind, with the remainder charging the battery. The battery reaches its upper SOC limit by 14:00 and the surplus is exported. In the evening peak (19:00–22:00), when the load rises to 600 kW, the battery discharges at up to 240 kW, the biogas generator runs at 150 kW and the wind turbines supply the rest. On an overcast monsoon day, PV falls below 150 kW, but wind and the biogas generator together cover over 70% of the demand, with grid imports of less than 90 kW in any hour. The fuel cell starts only during two or three hours per week, mostly in the early morning of calm, cloudy days, which explains its small annual output of 20,000 kWh.

G. Sensitivity Analysis

Table 8 gives the results of the one-at-a-time sensitivity analysis. The system is most sensitive to the discount rate, since the investment is capital-intensive: at a nominal 6% the LCOE falls to 0.092 US/kWh, while at 12% it rises to 0.119 US/kWh. A $\pm 20\%$ change of the annual load changes the LCOE by less than 3% because capacity scales almost proportionally, and the larger system benefits slightly from the fixed cost of the digester. A 20% rise in the PV cost increases the NPC by 4.1% (sensitivity coefficient 0.21 from Eq. (29)), a small effect compared to the 7.8% increase caused by a 15% reduction of the mean wind speed. This shows that the uncertainty in the wind resource is the most important technical risk and justifies a measurement campaign before final investment.

TABLE 8. Sensitivity Analysis of the Optimal Design

Parameter	Variation	NPC (US\$ M)	LCOE (US\$/kWh)	RF (%)
Base case	—	2.95	0.105	96.5
Annual load	+20%	3.51	0.104	95.8
Annual load	−20%	2.43	0.108	97.1
PV capital cost	+20%	3.07	0.109	96.5
PV capital cost	−20%	2.83	0.100	96.5
Mean wind speed	−15%	3.18	0.113	93.1
Mean wind speed	+15%	2.78	0.099	97.4
Nominal discount rate	6%	3.62	0.092	96.5
Nominal discount rate	12%	2.54	0.119	96.5

In every case the renewable fraction remains above the 90% constraint and the LPSP below 0.5%, so the design stays feasible without re-sizing when parameters change by the stated amounts. Only the −15% wind-speed case needed the optimizer to be re-run, and it shifted the solution by one turbine and 100 kWh of battery.

Discussion

The results demonstrate several points relevant to the planning of distributed generation. First, the complementary nature of the resources is the main driver of the cost reduction. PV and wind are partially anti-correlated in the monsoon, and the biogas generator covers the evening peak, which is the period when neither solar nor, often, wind output is high. This cuts the battery needed for a given LPSP: the optimised battery of 1,200 kWh stores about 6.2 hours of average load, whereas the PV–battery–grid design of Case C required a battery of nearly 2,900 kWh to approach the same reliability. As batteries account for 14% of the capital cost even in the optimised design, this reduction translates directly into lower NPC.

Second, the grid connection works as an inexpensive reliability and balancing resource. Grid imports of 3.5% of the load give much greater reliability than a stand-alone system would need to achieve at the same cost. Equally, the export of 83,300 kWh turns what would be curtailed energy into revenue. However, the benefit depends on regulatory conditions. If feed-in tariffs were removed, additional storage or demand response would be justified, and a re-run of the optimization with the revised tariff would be required.

Third, the comparison with the grid-only case should be read carefully. The LCOE of 0.105 US/kWh in the grid-only case were used, the grid-only supply would increase by 0.016 US/kWh, and the gap would shrink to about 0.003 US/kWh. These features indicate that the IRES is cost-competitive in a wider sense, even though it is not the cheapest source in a narrow accounting sense.

Fourth, the optimizer comparison gives support for the use of adaptive inertia. The gap in final NPC among algorithms was small (about 2.4%), which is expected for a smooth objective with a wide flat basin, but the differences in reliability of convergence and in computation time are meaningful when many scenarios must be evaluated, for example in a Monte-Carlo analysis or in a study of several sites. The standard deviation of 0.38% for the proposed optimizer indicates that a single run is usually adequate for practical purposes.

Limitations should be noted. The hourly time step can't resolve sub-hourly variability of PV and wind, which matters for converter sizing, frequency regulation and battery power rating. The battery degradation is modelled with a throughput limit and not with a full electrochemical ageing model. Feedstock availability for the biogas plant was assumed to be constant over the year, which is a simplification for crop-residue-based supply. The

dispatch strategy is rule-based, and the use of model predictive control might reduce grid purchases and battery ageing further. Finally, the case study applies to one site, and the sizes obtained should not be transferred directly to places with different resources or tariffs.

Conclusion

This paper developed and applied an optimal design methodology for an integrated renewable energy system intended for distributed power generation. Hourly models of PV, wind, biogas, fuel-cell, battery and converter units were combined with an economic model in which NPC and LCOE are minimised under constraints on LPSP, renewable fraction and component limits, and the combined problem was solved with an adaptive-inertia particle swarm optimizer.

For a grid-connected rural community with a peak demand of 612 kW, the optimal system consisted of 600 kW of PV, 400 kW of wind, a 150 kW biogas generator, a 25 kW fuel cell, 1,200 kWh of battery storage and a 450 kW converter. The system achieved an NPC of US\$ 2.95 million, an LCOE of 0.105 US\$/kWh, a renewable fraction of 96.5%, an LPSP of 0.20% and a 96.5% reduction in CO₂ emissions relative to grid supply. Compared with PV–diesel–battery and PV–wind–battery–grid alternatives, the proposed system had 31.5% and 6.1% lower NPC, respectively, and far lower emissions. The adaptive optimizer reached the best design in 48 iterations, with the smallest variation between independent runs, and the sensitivity analysis showed that the design stays feasible for $\pm 20\%$ changes in load and cost and $\pm 15\%$ changes in wind speed.

Future work will extend the model in four directions: sub-hourly simulation with explicit converter and frequency-control dynamics, an electrochemical battery ageing model, stochastic or robust optimization of resource and load uncertainty, and model predictive energy management. A field pilot with measured data would allow the predicted performance to be validated.

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