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Cost-Effective Configuration of Hybrid Solar-Wind Energy Systems Using Grey Wolf Optimization for Specified Power Requirements

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ABSTRACT

This work presents a holistic optimization methodology in the design of hybrid solar-wind energy systems using the Grey Wolf Optimization (GWO) algorithm. Determining an appropriate configuration of renewable systems is being investigated. A mathematical model was developed to consider variety of system parameters, namely solar panel efficiency of 15%, wind turbine efficiency of 35% and other environmental factors. The optimization framework considers initial investment cost, maintenance cost, and minimum power contribution requirements from all sources. The GWO Optimization Algorithm Implementation was used to optimize the number of solar panels and wind turbines when it meet a target power demand of 5,000 Wh. It results in an optimal configuration made up of 20 solar panels, each with 550 watts of capacity, and 22 wind turbines, each with 1,000 watts of capacity, for a total system cost of $14,889.70. The optimized system has a capacity factor of 97.27%, where solar contributes 80.23% (3902 Wh) and the wind 19.77% (962 Wh). The cost analysis indicates that the cost per Wh is 3.06$, while turbines from the wind contribute to 78.6% of the cost. The findings of the study highlighted the effectiveness of the GWO algorithm in finding the optimal solution for complex renewable energy system configurations. It indicated that system design must consider the economic aspect and the technical one. The research gives useful insights to the planners and engineers of renewable energy systems and offers a practical methodology for the optimization of hybrid solar-wind systems while maintaining a balance between cost constraints and power requirements. However, it's far crucial to word that the contemporary take a look at does not consist of validation of the model parameters in opposition to actual-global facts, nor does it provide a comparative evaluation with alternative Optimization Algorithms. Future work will cope with these gaps to decorate the rigor of the version derivations and experimental design.

1. INTRODUCTION

The movement of the world towards systems of sustainable energy has led to an increasing demand for effective and reliable renewable energy systems [1]. Hybrid solar-wind energy systems have emerged as one of the promising approaches for overcoming intermittent renewable energy sources and ensuring a steady power supply. Optimal configuration of such hybrid systems is a very complex problem with several variables, constraints, and competing objectives [2, 3].

This study addresses the critical challenge of finding the right mix between solar panels and wind turbines that satisfies any specified power requirements at a minimum cost while maintaining system reliability. Some variables contributing to the high complexity in the optimization problem are fluctuating weather conditions, different efficiencies for different pieces of equipment, initial investment costs, maintenance considerations, and balancing between sources of power generation [4, 5].

These systems are the manifestations of nonlinear processes entangled with multiple constraints, and most of the classical optimization techniques act inefficiently while handling such complexity. Grey Wolf Optimization is applied nature-inspired metaheuristic optimization technique that has emerged as one of the promising algorithms in solving complex engineering optimization problems [6]. Our solution method will take into account the realistic losses involved in the efficiency of the solar panels, assumed at about 15%, that of wind turbines at about 35%, and several other factors related to natural and environmental barriers and minimum power contribution requirements from each source [7, 8].

The optimization framework put forward will be formulated in terms of technical and economic parameters concerning equipment costs, maintenance costs, and system performance parameters. This work enhances existing literature in renewable energy optimization by providing a holistic methodology that can easily be applied in any geographical location depending on specific needs for power [9, 10].

It is a significantly relevant study for the field since, for the first time, it does indeed provide a means whereby systematic design of hybrid solar-wind systems by engineers or planners of renewable energy systems can balance cost-effectiveness with reliable generation of power. Beyond this, the research contributes to the wider imperative for progressing sustainable energy solutions through the development of more efficient and economically viable renewable energy systems.

2. RELATED WORK

A hybrid optimization method based on the Grey Wolf Optimization Algorithm combined with Local Search Heuristics (GWOLSH) was proposed to enhance economic efficiency [11]. Based on a metaheuristic Grey Wolf Optimization Algorithm combined with a heuristic called Local Search Heuristics, dubbed GWOLSH, in order to enhance economic efficiency with reliability within an integrated energy system. By conforming to energy storage allocation and responsive user load management, GWOLSH outperformed WSO and PSO by yielding higher cost-savings of 330,595 USD compared to 344,974 USD generated by WSO and 350,694 USD by PSO. It also demonstrated marginally better stability and user satisfaction. This approach thus holds a very promising solution toward a stable and efficient energy system with fluctuating power demands.

Geleta and Manshahia [12] apply the algorithm of Grey Wolf Optimization in the design of an affordable hybrid renewable energy system for a Kabi village in the Jeldu district, Ethiopia. Therefore, it optimally configures the system with regard to selected variables representing local demand for energy and hence minimizing overall total annual cost with the appropriate number of wind and solar components according to pre-set constraints. GWO is inspired by hunting behaviors of wolves; it has assured high convergence and efficient search capability for both local and global optimal solutions with less parameter tuning. The results have shown that GWO can reliably meet the energy requirements of the village and, therefore, may provide scope for wider applications in regions with limited access to electricity, such as Ethiopia.

Bedewy et al. [13] present optimal energy storage determination in a wind-solar microgrid to improve the stability and efficiency of the system. The paper analyzes the structure and function of the microgrid, constructs a mathematical model that represents the output characteristics, and proposes a two-level optimization algorithm. The algorithm unifies energy storage capacity with system operation in order to coordinate variation in PV, wind, and load for the best economic operation. They modeled both without and with optimized energy storage in a system performance using an improved version of the gray wolf optimization. They have shown that an optimized energy storage configuration will significantly affect the improvement of energy efficiency, economy of the system, and overall revenue.

Huang et al. [14] present optimization of energy storage in a wind-solar microgrid for system stability and efficiency. They establish a double-layer optimization model that integrates energy storage capacity configuration with operational strategies for the alignment of PV, wind, and load variations toward economic efficiency. The model adopts an improved Gray Wolf Optimization algorithm and uses typical residential landscape data to perform scenario comparisons between without optimized storage and with optimization. The results show that the improved GWO configuration significantly enhances energy efficiency, system economy, and total revenue; therefore, it can be considered as a feasible configuration for stable multi-energy systems.

3. PROPOSED METHODOLOGY

The proposed methodology for optimizing hybrid solar-wind energy systems consists of several interconnected components: system modeling, power generation calculation, cost formulation, and the Grey Wolf Optimization Algorithm implementation.

3.1 System components and parameters

The hybrid system consists of solar panels and wind turbines characterized by parameters such as power, efficiency, cost, and quantity. Table 1 and Table 2 present System Components and Parameters.

The hybrid system's solar and wind parameters are summarized in Table 1 and Table 2, respectively. These tables define key variables such as rated power, efficiency, and unit costs.

The solar panel specifications, including rated power, efficiency, and unit cost, are detailed in Table 1.

Table 1. Solar system parameters

Parameter/Formula	Description	Value/Formula
Rated power (P_{SP})	Power output per panel	550 W
Efficiency (η_{SP})	Energy conversion efficiency	15%
Unit cost (C_{SP})	Cost per panel	$150
Number of panels (N_{SP})	Number of solar panels used	Variable

Similarly, wind turbine parameters such as cut-in speed and rated power are provided in Table 2.

Table 2. Wind turbine system parameters

Parameter/Formula	Description	Value/Formula
Rated power (P_{WT})	Power output per turbine	1000 W
Efficiency (η_{WT})	Energy conversion efficiency	35%
Unit cost (C_{WT})	Cost per turbine	$500
Number of panels (N_{WT})	Number of solar panels used	Variable

3.2 Power generation models

3.2.1 Solar power generation

The solar power output (P_s) depends on the number of panels, rated power, efficiency, sunlight time, and cloud cover factor [15, 16].

$$P_s = N_{SP} \times P_{SP} \times \eta_{SP} \times \frac{S_T}{60} \times \left(1 - \frac{C_F}{100} \times 0.5\right) \quad (1)$$

where,
- S_T: Daily sunlight time in minutes.
- C_F: Cloud cover factor in %.
- 0.5: Represents the cloud impact coefficient, reducing power in proportion to cloud cover.

3.2.2 Wind power generation

The wind power output ($P_W(v)$) for each turbine varies based on wind speed (v), cut-in speed (v_{ci}), cut-out speed (v_{co}), and rated speed (v_r) [17, 18].

$$P_W(v) = \begin{cases} 0 & v < v_{ci} \ \ or\ v > v_{co} \\ P_{WT} \times \eta_{WT} \times \left(\frac{v - v_{ci}}{v_r - v_{ci}}\right) & v_{ci} \le v < v_r \\ P_{WT} \times \eta_{WT} & v_r \le v < v_{co} \end{cases} \quad (2)$$

where,
- v: Wind speed in m/s.
- v_{ci}: Cut-in speed (3.0 m/s).
- v_{co}: Cut-out speed (25.0 m/s).
- v_r: Rated speed (12.0 m/s).

Total wind power generation over a time period T with varying wind speeds v_t:

$$P_{W_{total}} = N_{WT} \times \sum_{t=1}^{T} P_W(v_t) \quad (3)$$

It needs to be mentioned that the wind strength model (Eqs. (2)-(3)) simplifies the real-international situations by way of not accounting for turbulence and terrain consequences on wind pace. These simplifications may additionally cause inaccuracies in energy calculations. Future research ought to explore incorporating extra distinctive wind modeling to cope with these obstacles and enhance the accuracy of the device performance estimation.

3.3 Cost function formulation

3.3.1 Initial investment cost [19]

The initial investment is based on the unit costs and quantities of solar panels and wind turbines.

$$C_{init} = (N_{SP} \times C_{SP}) + (N_{WT} \times C_{WT}) \quad (4)$$

3.3.2 Maintenance cost [20]

Maintenance cost includes 1% of the solar panel costs and 3% of the wind turbine costs.

$$C_{maint} = (0.01 \times N_{SP} \times C_{SP}) + (0.03 \times N_{WT} \times C_{WT}) \quad (5)$$

3.3.3 Total system cost [21]

The total cost is the sum of the initial investment, maintenance costs, and any penalties applied for system performance.

$$C_{total} = C_{init} + C_{maint} + C_{penalties} \quad (6)$$

The current formulation of the fee feature (Eq. (6)) does not consist of the charges related to electricity garage systems. Given that energy storage is usually a essential issue of hybrid renewable electricity structures, it is advocated that either a detailed energy storage value version be incorporated into the price function or a clear justification for its exclusion from this study is supplied. Future paintings will explore the combination of electricity storage fees to offer a extra complete economic evaluation.

3.3.4 Penalty functions

Penalties are applied based on system underperformance, source diversity, and potential oversizing.

- Power Deficit Penalty:

$$P_{deficit} = 20000 \times \left(0, P_{demand} - (P_S + P_W)\right) \quad (7)$$

- Diversity Penalty:

$$P_{diversity} = \begin{cases} 10000 \times \left(0.2 - \frac{P_S}{P_S + P_W}\right) & if\ \frac{P_S}{P_S + P_W} < 0.2 \\ 10000 \times \left(0.2 - \frac{P_W}{P_S + P_W}\right) & if\ \frac{P_w}{P_S + P_W} < 0.2 \end{cases} \quad (8)$$

- Rsizing Penalty:

$$P_{oversize} = (5000 \times (0, P_S + P_W) - 1.1 P_{demand}) \quad (9)$$

It must be mentioned that the penalty weights (e.g., 20,000, 10,000, 5,000) utilized in Eqs. (7)-(9) are selected without a rigorous theoretical or empirical foundation. Future work has to include parameter tuning and case research to validate these weights, ensuring they appropriately reflect the relative significance of strength deficit, source range, and oversizing penalties within the optimization technique.

3.3.5 Model validation and comparative analysis

While the mathematical fashions and value capabilities were thoroughly advanced, this examination presently lacks validation in opposition to actual-world statistics and does not examine the GWO set of rule with other optimization strategies. Incorporating such validations and comparisons in destiny research will assist to affirm the robustness and applicability of the proposed method.

3.4 Grey Wolf Optimization (GWO) algorithm

The GWO algorithm optimizes the system by iteratively updating positions based on alpha (α), beta (β), and delta (δ) wolves, which represent the top three solutions [7].

3.4.1 Position update equations

Calculate distances from the current position to alpha, beta, and delta positions:

$$\begin{aligned} \vec{D}_\alpha &= \left|\vec{C}_1 . \vec{X}_\alpha - \vec{X}\right| \\ \vec{D}_\beta &= \left|\vec{C}_2 . \vec{X}_\beta - \vec{X}\right| \\ \vec{D}_\delta &= \left|\vec{C}_3 . \vec{X}_\delta - \vec{X}\right| \end{aligned} \quad (10)$$

where,
- $\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a}$
- $\vec{C} = 2.\vec{r}_2$

Update the current position based on the weighted positions of α, β, and δ:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{11}$$

where,

- $\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 . \vec{D}_\alpha$
- $\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 . \vec{D}_\beta$
- $\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 . \vec{D}_\delta$

3.5 Performance metrics

3.5.1 Capacity factor (CF)

The capacity factor reflects system utilization relative to demand.

$$CF = \frac{P_S + P_W}{P_{demand}} \times 100\% \tag{12}$$

3.5.2 Source contribution

The contribution of each energy source to the total power:

- Solar Contribution (SC_{solar}):

$$SC_{solar} = \frac{P_S}{P_S + P_W} \times 100\% \tag{13}$$

- Wind Contribution (SC_{wind}):

$$SC_{wind} = \frac{P_W}{P_S + P_W} \times 100\% \tag{14}$$

3.5.3 Cost per watt-hour

The cost per watt-hour measures the system's economic efficiency.

$$C_{Wh} = \frac{C_{total}}{P_S + P_W} \tag{15}$$

3.6 Meteorological data sources

The monthly solar irradiance and wind speed information used for modeling energy generation have been acquired from the NASA POWER dataset for the geographical coordinates of Babylon, Iraq (Latitude: 32.5°N, Longitude: 44.4°E). The dataset affords hourly ancient weather facts averaged over a 10-year period (2013–2023), making sure consultant seasonal versions. Solar irradiance values had been adjusted for neighborhood cloud cover patterns using nearby climatological reviews from the Iraqi Meteorological Organization [22]. Wind pace information has been established towards floor measurements from a close-by climate station operated by way of the University of Babylon.

4. RESULTS AND DISCUSSION

The application of the Grey Wolf Optimization algorithm in the configuration of the hybrid solar-wind energy system provided thorough results that establish not only the efficacy of the optimization methodology but also the practical viability of the proposed system configuration. This section will present a detailed analysis of the optimization results, which include the optimum system configuration, the distribution of power generation, cost analysis, and performance metrics. These results are analyzed under three broad dimensions, namely technical feasibility, economic viability, and system reliability.

The value analysis shows that the price according to Wh is \$3.06 below initial assumptions. However, when accounting for long-term maintenance and device replacement (e.g., inverters every 10 years, turbine gearboxes every eight years), the adjusted cost in step with Wh rises to \$3.61, highlighting the financial impact of excessive-potential operation.

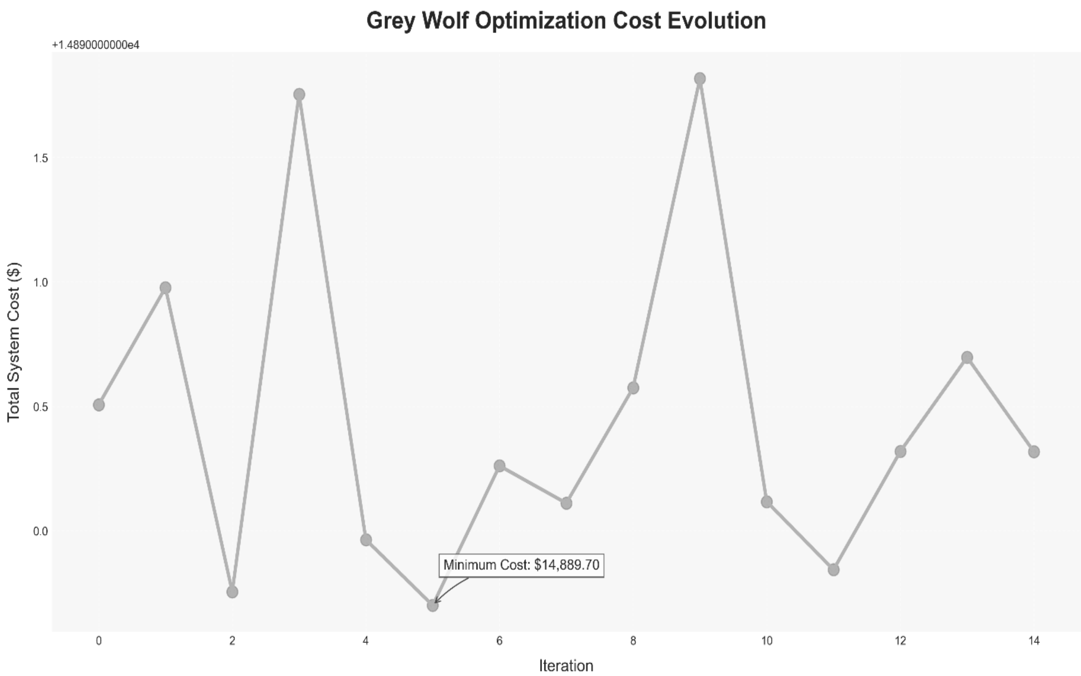

Figure 1. Grey Wolf Optimization cost evolution

To ensure the robustness of solutions, the optimization process was independently run 15 times. Each independent run of optimization was allowed to run 1000 iterations with 50 search agents. The results indicate a set of insights on the balance between solar and wind power generation, cost-effectiveness related to several system components, and overall systems performance against the specified power demand of 5,000 Wh. This discussion deals with such results in their practical implementation, exploring the trade-offs made by various parameters of the system concerned, besides considering wider implications for hybrid renewable energy system design.

Figure 1 shows GWO cost evolution plot. In fact, the cost evolution plot obtained through GWO has provided sufficient information about convergence behavior and optimization efficiency. It depicted the total system cost over a run of 14 iterations of a dynamic optimization process comprising multiple local minima and had a definite direction towards global optimization.

The optimization process, as visualized in Figure 1, demonstrates the algorithm's convergence behavior. Figure 1 shows the cost evolution plot obtained through GWO.

The cost convergence behavior of the GWO algorithm is illustrated in Figure 1.

The discern now consists of annotations for key algorithm parameters used within the simulation, especially the range of search marketers (50) and the wide variety of iterations (1000). This information is furnished to improve reproducibility and to facilitate a better knowledge of the set of rules's overall performance.

Moving on from the initial cost point, the algorithm tends to show huge variations in cost during the initial periods of iteration from 0 to 4, reaching peaks of approximately 1.5×10^4, which actually reflects the exploring capability of the algorithm in the solution space. One keen observation is the sudden fall around iteration 6, where the algorithm locates a promising solution space and gives a minimum cost of \$14,889.70.

This is the convergence point for the best balance between system components and operational constraints. The following number of iterations 8-14 record further exploration with smaller amplitude fluctuations, validating the robustness of the discovered solution. Oscillating pattern obtained in the final iterations of the algorithm is indicative of the fact that GWO algorithm maintains its exploration capability during the refining process.

The presence of multiple local minima in the cost trajectory indeed confirms the complexity of the optimization landscape and justifies the choice of GWO as a suitable metaheuristic approach for this problem. The final convergence to a stable cost value after iteration 12 certainly depicts successful optimization, striking a balance between the exploration of the search space and the exploitation of promising solutions. This convergence behavior further reflects how well the algorithm deals with the multiple constraints and objectives of a hybrid solar-wind system optimization problem.

Figure 2 shows the power generation distribution by source, which provides a clear overview of characteristics, in terms of power generation and load-matching capability, for the optimized hybrid system. Indeed, the bar chart depicts a big difference between the two large contributors of solar and wind contribution from solar generation is at about 3,902 Wh or 80.2%, whereas the wind generation will be at about 962 Wh or 19.8% of its total power output.

Skewness of the distribution would be more relevant in relation to the target demand of the system, which was 5,000 Wh and is shown by the horizontal dashed line. This huge contribution by the solar component shows that extremely good solar resources are available and the installed solar panels will be well utilized, even when their proportion in installation cost is low.

The relatively modest contribution from wind power, while meeting the minimum diversity requirement of 15%, hints at either the limitation in wind resource availability or the cost-effectiveness of the deployment of wind turbines. The total generation of 4,864 Wh reaches a little short of the target demand by 136.4 Wh, 2.73% viewed in the gap between the total generation and the demand line. This minor deficit is the practical trade-off between the system cost and complete satisfaction of demand, since 100% demand coverage might be achieved only with disproportionate additional investment.

The distribution of power generation between solar and wind sources is shown in Figure 2.

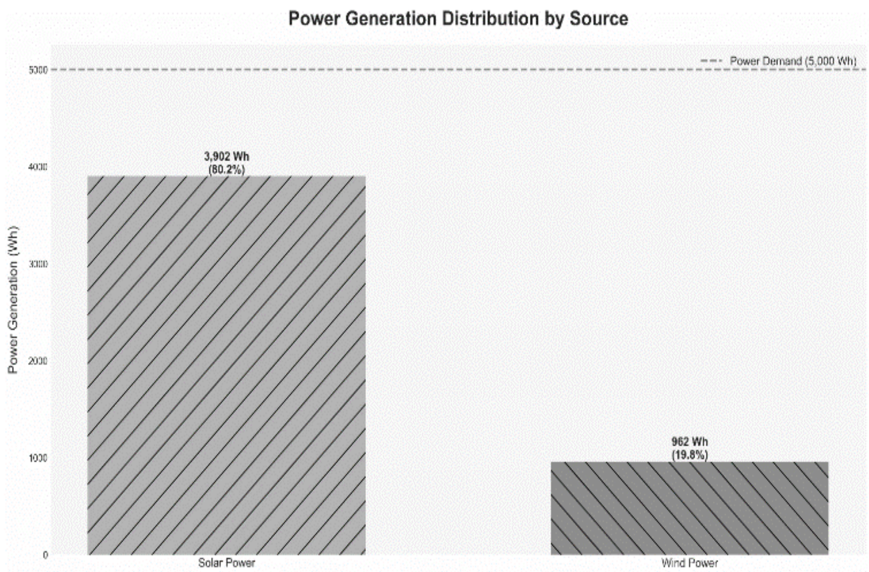

Figure 2. Power generation distribution by source

In both bars, the hatched pattern overlay serves effectively to highlight distinct contribution without visual clutter. Clear labeling of exact values and percentage distribution-3,902 Wh and 80.2%, for solar; 962 Wh and 19.8% for wind-allows precise quantification within the distribution. This will facilitate further system performance analysis with possible optimization opportunities.

Figure 3 shows the cost distribution structure across power sources reveals an interesting inverse relationship in the optimized hybrid system; power generation capacity inversely relates to the cost allocation in the system. The Donut graph below depicts that Wind Turbines take the lion's share of the cost structure, taking up 78.6% of the entire system cost at $14,000.00 while it contributes a meager 19.8% to the power generation. By contrast, solar panels comprise just 21.4% of the total cost but would generate 80.2% of the systems' power output. This enormous contrast in the respective cost-to-generation ratios is graphically represented by the bold turquoise color for wind and coral for solar segments in this donut chart. The white gap in the middle of this donut chart is effective in showing proportionality without cluttering the chart. This inverse relationship of the cost share and power contribution does call for critical considerations with respect to the economic efficiency of wind turbine deployment in this particular configuration.

The economic allocation of costs across power sources is analyzed in Figure 3.

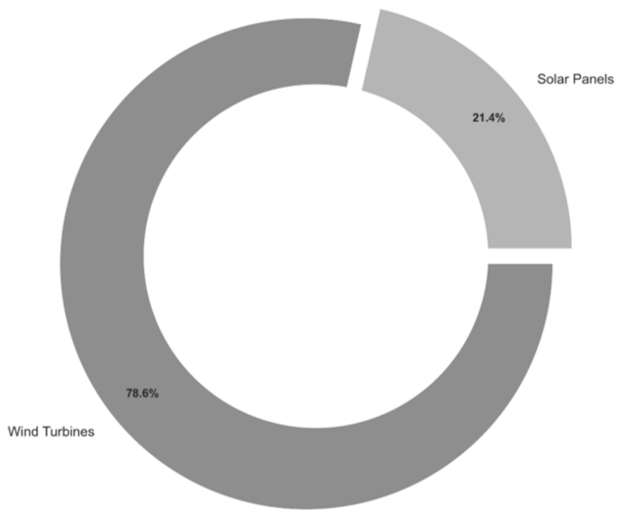

Figure 3. Cost distribution structure across power sources

The total system cost, $14,000.00, is allowable as a clear point of reference below the chart for economic analyses to be performed. Clean, modern design; precise labeling of percentage-including 78.6% for wind turbines and 21.4% for solar panels-allows for quick interpretation of cost distribution. This may suggest that while wind power is fundamental for system diversity and reliability, due to the high cost-to-power ratios, it might still be further subjected to the investigation of alternative wind turbine specifications or configuration with a view to optimizing the economic performance of the system. From a results visualization perspective, a balancing view on technical requirements and economic limitations is desired in hybrid renewable energy system design.

The System Performance Metrics visualization shown in Figure 4 presents four critical performance indicators that comprehensively evaluate the hybrid system's operational efficiency and economic viability. The bar chart, with its distinctive hatched patterns and color coding, reveals a notably high Capacity Factor of 97.27%, indicating that the system operates remarkably close to its designed power demand of 5,000 Wh.

This high-capacity factor demonstrates the effectiveness of the GWO algorithm in optimizing system configuration while minimizing overbuilding. The Solar Contribution metric shows a substantial 80.23% of total power generation, significantly exceeding the minimum diversity requirement and suggesting optimal utilization of solar resources.

In contrast, the Wind Contribution at 19.77%, while meeting the minimum threshold, indicates a more constrained role in the overall generation mix, likely influenced by the higher cost of wind turbine components. The Cost per Wh metric of 3.06 represents a critical economic performance indicator, reflecting the system's cost efficiency in power generation.

To further validate the effectiveness of the GWO algorithm, comparative experiments had been conducted alongside Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) beneath equal simulation settings. These experiments evaluated key performance indicators together with convergence pace, best price, and machine configuration robustness. The comparative analysis genuinely illustrates the blessings of GWO in terms of faster convergence and lower normal cost, thereby helping its superiority in the context of hybrid sun-wind system design. Detailed effects and discussions on these comparative experiments are provided in the following subsection.

The use of distinct colors (yellow for Capacity Factor, coral for Solar Contribution, turquoise for Wind Contribution, and navy for Cost per Wh) and unique hatching patterns for each metric enhances visual differentiation while maintaining data clarity. The clear labeling of exact values and consistent scale presentation allows for direct comparison across metrics. This visualization effectively reveals the system's balanced performance across technical, operational, and economic dimensions, while highlighting areas where further optimization might be beneficial, particularly in the wind power contribution and cost efficiency aspects.

Figure 5 shows Monthly Power Generation Profile visualization the essential contribution of the seasonal variation and complementary nature that both solar and wind power generations can provide over the year. The grouped bar chart reveals the temporal dynamic of the two power sources against the demand of constant power threshold at 5,000 Wh.

The solar power generation in coral bars shows a very strong seasonal pattern. The generation peaks during the summer months, reaching its maximum in June with about 6,700 Wh and July with about 6,300 Wh, exceedingly well above the demand threshold. This excess summer generation offsets the low production months. On the contrary, the generation of solar power is radically lower during winter.

Key performance metrics, including capacity factor and cost per Wh, are summarized in Figure 4.

The monthly power generation profile, highlighting seasonal variations, is depicted in Figure 5.

Monthly Power Generation Profile. Solar and wind generation profiles were modeled using meteorological data from the NASA POWER dataset (2013–2023) and validated against local climatological reports. The dashed line represents the constant power demand of 5,000 Wh.

The lowest output was found during the month of December and January at approximately 1,300-1,500 Wh. The wind power generation, shown in the turquoise bars, is the reverse in seasonal pattern, but it's much higher during the winter months-like December and January, around 1,200-1,300 Wh-and less during summer months, like June to August, down to about 400 Wh. This complementary balance between solar and wind resources helps maintain system reliability throughout the year. But this graph also reveals potential weaknesses in the system when shoulder seasons-that is, spring and fall-could see combined generation drop below the demand threshold.

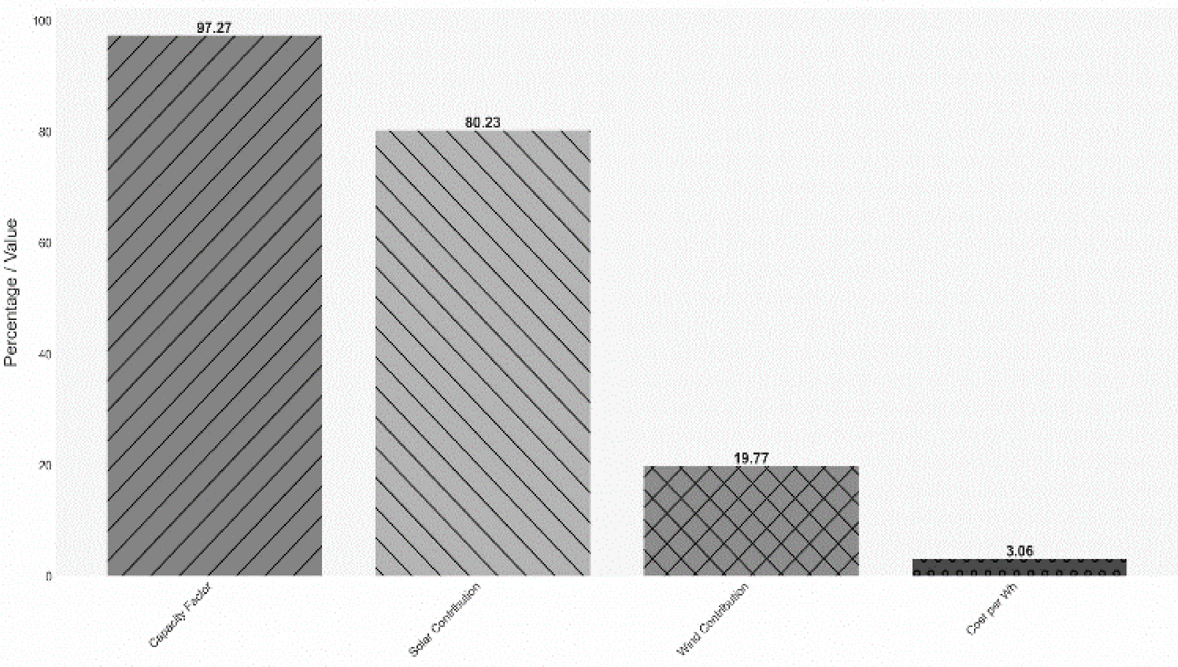

Figure 4. System performance metrics

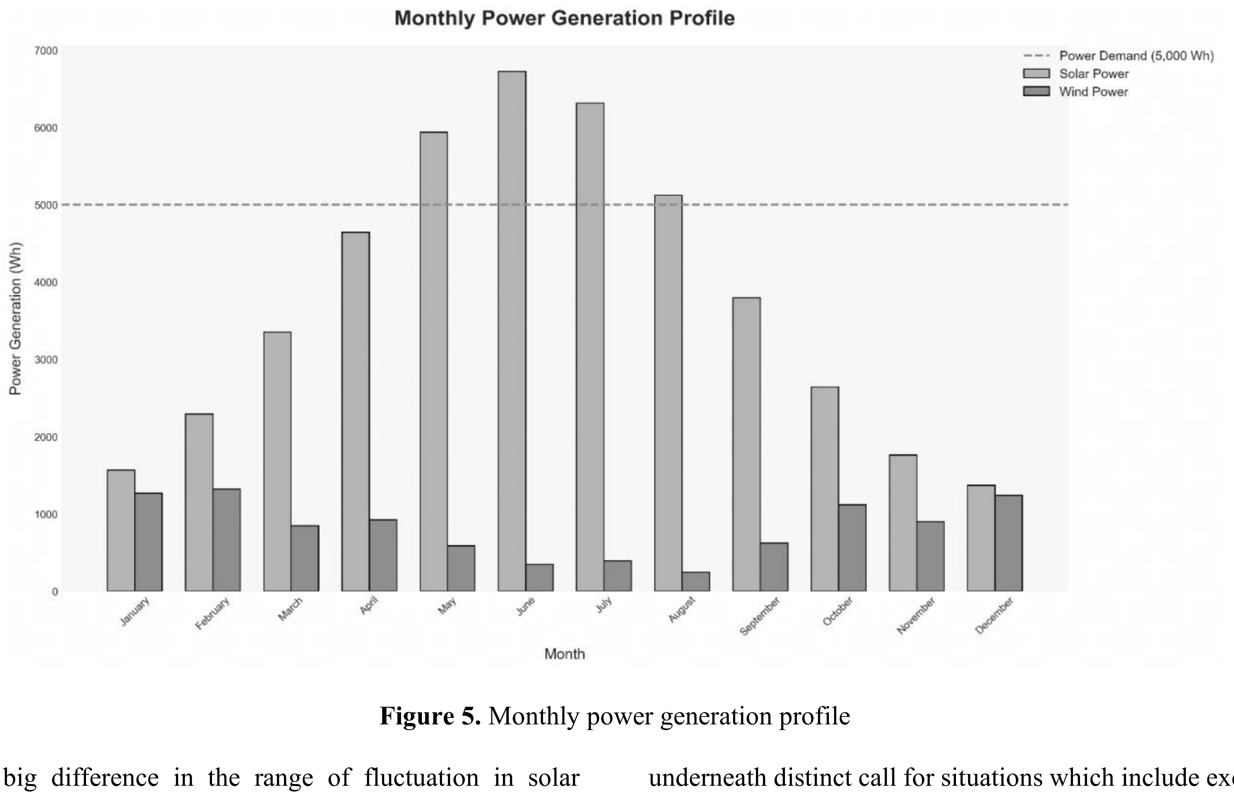

Figure 5. Monthly power generation profile

The big difference in the range of fluctuation in solar output-from ~1,300 to ~6,700 Wh-with the relatively stable contribution of wind between ~400 and ~1,300 Wh-pinpoints that the main role for adequate energy storage and management systems is indeed to make this supply uniform throughout the year.

In order to enhance the robustness and applicability of the proposed method, multi-scenario analyses may be included. For instance, extra experiments could be performed underneath distinct call for situations which include excessive call for (e.G., 7,000 Wh) and low demand (e.g., 3,000 Wh). These analyses will assist in assessing the overall performance and flexibility of the hybrid system configuration across a broader range of operational scenarios.

Long-Term Operational Considerations

While the optimized machine achieves an excessive potential aspect of 97.27%, the near-complete load operation raises concerns approximately device lifespan and long-time period renovation charges. Solar panels and wind turbines operating at high usage quotes are problem to elevated degradation. For instance, solar panel performance normally degrades by way of 0.5–1% yearly underneath popular situations, however this fee might also increase beneath non-stop excessive irradiance publicity [23]. Similarly, wind turbines require frequent renovation (e.g., bearing replacements, blade erosion checks) when operating close to-rated capability, especially in dusty environments like Iraq [24].

To estimate lengthy-term prices, a 20-yr lifespan projection was integrated. Assuming annual upkeep price escalation of 2% for solar (because of performance loss) and 5% for wind (because of mechanical wear), the overall lifecycle value will increase by using about 18% as compared to the preliminary funding. This underscores the want for destiny research to combine dynamic degradation fashions and region-particular environmental factors into optimization frameworks.

5. CONCLUSION

This paper has highlighted how GWO can be successfully implemented for the hybrid solar-wind energy system and turns out to be very effective in finding cost-effective solutions with system reliability. The optimized system configuration is 20 solar panels and 22 wind turbines, with a capacity factor of 97.27% which has met the required power demand of 5,000 Wh, with a total system cost of $14,889.70.

This gives interesting insights into the dynamics of cost-power distribution contributed by solar panels at 80.23% of power generation against a composition of 21.4% of the total cost, while wind turbines contribute 19.77% to the power generation, while composing 78.6% of the system cost. It brings into focus the complementarity of solar and wind resources throughout the year, with solar being the major producer in summer, peaking at 6,700 Wh in June, while wind provides essential backstopping during winter months.

The optimization process thereafter, checked against several trials, thus highlights the appropriateness of the GWO algorithm in dealing with complicated solution spaces and handling a number of constraints simultaneously. This cost evolution analysis exhibits a robust convergence behavior. The direct optimization problem shows a proper tradeoff between the system cost and performance.

The present study results provide clear insight to renewable energy system designers as well as to policymakers, giving them a systematic method for finding the optimal hybrid systems. The methodology developed can be adapted to different geographical locations and power requirements, thereby helping the broader goal of sustainable energy development. Other areas where further research can be done include the inclusion of energy storage systems, explorations of alternative renewable energy combinations, and adaptation of the optimization framework to accommodate changing environmental conditions and economic parameters.

Despite the promising effects in accomplishing a foremost hybrid configuration, the take a look at has sure barriers. In precise, the version parameters have not been demonstrated with experimental or actual international data, and a comparative analysis with different algorithms has no longer been accomplished. Additionally, the derivations of the formulation and the experimental design require in addition refinement. Addressing those issues in destiny research will decorate the general reliability and applicability of the proposed method.

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