

Carbon Assessment and Carbon Reduction Potential Analysis of Rural Integrated Energy System Based on Reinforcement Learning

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Abstract. Recent years have seen Reinforcement Learning (RL) excel in real-time decision-making and coordinated optimization of complex energy systems. Scholars have applied RL to carbon emission optimization in urban microgrids and industrial parks, but a gap exists in rural integrated energy systems (RIES) regarding carbon assessment and reduction potential analysis—rural energy data is coarse and variable, and rural social-technical coupling is complex, demanding RL for dynamic trade-offs. This study introduces an RL framework to build a "data-driven-model collaboration-strategy evolution" system, uses heuristic algorithms for RIES carbon accounting, scenario simulation and reduction evaluation, compares with algorithms like greedy to find the optimal one, and supports precise carbon reduction and rural revitalization. Results show that the proposed heuristic algorithm reduces costs by 32.3% and carbon emissions by 32.1% compared to the pure diesel algorithm, and balances economic efficiency and low-carbon benefits more effectively than the greedy algorithm.

Keywords: Rural Integrated energy systems, Carbon Assessment, Carbon Reduction, Reinforcement Learning

1. Introduction

Under the dual goals of the "dual carbon" strategy and rural revitalization, the low-carbon transition of Rural Integrated Energy Systems (RIES) has become a core academic and management concern. Rural areas boast abundant renewable resources (rooftop photovoltaics, agroforestry waste, small hydropower), providing great potential for building multi-energy complementary "source-network-load-storage" integrated systems. However, existing research relies on static accounting or traditional optimization models for rural carbon emission assessment and reduction pathway design, failing to fully capture RIES operation characteristics like low inertia vulnerability, multi-energy flow coupling, and spatiotemporal heterogeneity.

This study aims to tackle two core issues: inaccurate RIES carbon assessment from static/traditional models (missing key operational features), and lack of dynamic mechanisms to balance economic costs and carbon reduction in rural energy scheduling. To solve these, it integrates

two methods: a Reinforcement Learning (RL) framework for "data-driven-model collaboration-strategy evolution" optimization, and Heuristic-Dynamic Bayesian Network (DBN) for RIES carbon accounting, scenario simulation and reduction evaluation—comparing with greedy, random and pure diesel algorithms to select the optimal strategy. The research addresses the gap in RIES carbon assessment by RL, offering a dynamic tool for scheduling rural energy-carbon and facilitating precise carbon reduction and a low-carbon transition alongside rural revitalization.

2. Literature review

Chen et al. proposes "rural biomass energy system optimization considering carbon trading" and calculates carbon trading costs via $(\min(C_{\text{energy}} + C_{\text{op}} + C_{\text{carbon}}) = (E_{\text{CH}_4} \text{GWP}_{\text{CH}_4} + E_{\text{CO}_2} \times \text{GWP}_{\text{CO}_2}))$. This study's septic tank coupling model draws on this logic, simplifies biomass combustion's indirect carbon emission coefficient, and focuses on septic tanks' direct CH₄ and CO₂ emissions [1].

Huang et al. puts forward "collaborative modeling of biogas combined heat and power (CHP) and rural energy systems" and constructs a thermoelectric calculation framework including biogas low calorific value and equipment efficiency. This study's daily biogas production ($P_{\text{biogas}} = r_{\text{biogas}} \times V_{\text{biogas}}$) and gas turbine thermoelectric models ($Q_{\text{O}} = \eta_{\text{emt}} \times P_{\text{biogas}} \times L_{\text{g}}$, $E_{\text{O}} = \eta_{\text{pg}} \times P_{\text{biogas}} \times L_{\text{g}}$) draw on its principles, simplify dynamic parameters like rainfall and heat dissipation, and retain static parameters like gas production efficiency [2].

Fu and Li et al present "synergistic accounting of energy consumption and carbon emissions of multi-equipment in agricultural microgrids" and build a greenhouse energy consumption model: $(E_{\text{hc}} = \text{Daily electricity consumption} \times \text{Carbon Emission Factor})$. This study's greenhouse model adopts its associated thinking, simplifies crop cycles and equipment start-stop losses, and retains heating/cooling energy consumption and grid carbon factors [3-4].

Sun and Lu et al. propose "full-chain modeling of gas production and power generation from rural biomass pyrolysis and gasification" and establish a material-energy balance model. This study's biomass gas production rate ($V_{\text{f,t}} = \beta_{\text{g}} \times M_{\text{f,t}} \times \eta_{\text{g}}$) and power generation model ($E_{\text{f}} = \lambda_{\text{g}} \times Q_{\text{g}} \times \eta_{\text{pg}}$) draw on its logic, simplify parameters like biomass types and gasification temperature-pressure, and retain processing capacity and gasification coefficients [5-6].

3. Methodology

3.1. Model solving algorithm and core formula

The core algorithm employed is the Heuristic-Dynamic Bayesian Network (DBN), which follows a "data-driven modeling-heuristic optimization" approach. Initially, the DBN processes the uncertain correlations among variables in the rural energy system, such as photovoltaic output, biogas production, and carbon emissions. Subsequently, a heuristic algorithm is utilized to optimize the system, taking into account carbon costs.

Multivariate Correlation Modeling utilizes a Bayesian Network (BN) to decompose the multivariate joint probability.

$$P_{\text{BN}}(X_1, X_2, \dots, X_n) = \prod_{m=1}^n P(x_m | \text{Pa}(x_m)) \quad (1)$$

where X_1 (photovoltaic output), X_2 (biogas production), X_n (system carbon emissions) are key variables; $(P(x_m|Pa(x_m)))$ is conditional probability under "parent nodes" (e.g. X_2 , diesel output X_4 , quantifying variables' synergistic impact on carbon emissions [7-8].

The optimization objective function aims to minimize the sum of "economic costs + carbon costs," expressed as:

$$\min \sum_{t=1}^T (d_{o,t} C_d + P_{\text{gridpower},t} \lambda_{p,t}) \quad (2)$$

where $d_{o,t}$ (diesel output, kW) represents direct high-carbon source; $P_{\text{gridpower},t}$ (grid-purchased power, kW) affects indirect carbon emissions. The economic parameters include C_d (diesel cost, CNY/kWh), $\lambda_{p,t}$ (time-of-use price, CNY/kWh), with T denoting the total time steps (e.g., 72h) [9-10]. The core constraints include power balance, ensuring that the load demand equals the sum of photovoltaic output, energy storage charge/discharge, $d_{o,t}$ and $P_{\text{gridpower},t}$ [11]. Additionally, energy storage SOC is $20\% \leq \text{SOC}_t \leq 90\%$, and the diesel power must satisfy $10\text{kW} \leq d_{o,t} \leq 100\text{kW}$ [12].

3.2. Introduction to the experimental process

The code in this study is built using Python's Anaconda, and Table 1 shows the experimental data.

Table 1. Detailed data table

Data Type	Specific values
Simulation Time	3 days (72 hours)
Photovoltaic Data	6-18kW during the day (20-50 hours), 0kW at night
Load Data	The base load is 10 ± 3 kW, with an increase of 15 ± 4 kW during meal periods (7-9, 12-14, 18-20 hours), and at night (22-6 hours), it is 60% of the base load
Electricity Price Data	0.8 yuan/kWh during peak hours (8-12, 17-21 hours), 0.5 yuan/kWh during normal hours (12-17, 21-23 hours), and 0.3 yuan/kWh in trough hours (the rest of the time)
Data related to carbon emissions	The carbon emission coefficient of diesel generators is $2.6\text{kgCO}_2/\text{kWh}$, and the carbon price is 0.2 yuan/kgCO ₂

The steps for code execution are as follows. First, generate photovoltaic, load, and electricity price data for a period of 3 days, which is equivalent to 72 hours. Next, conduct energy scheduling simulations utilizing four distinct algorithms: the heuristic algorithm (HeuristicManager), the greedy algorithm (GreedyManager), the random algorithm (RandomManager), and the pure diesel algorithm (DieselOnlyManager). Following this, output the results for each algorithm, including costs, carbon emissions, and energy distribution. Finally, visualize and compare the total cost, total CO₂ emissions, energy source distribution, and hourly data across all algorithms.

The data processing procedure is as follows. First, determine the battery charging and discharging, diesel generator output, and grid electricity purchase based on the difference between photovoltaic output and load demand every hour. Next, calculate the hourly costs, which include grid electricity purchase costs and diesel costs, as well as the corresponding carbon emissions. Finally, summarize the data for each time period to generate statistical results and visual charts, which will be used for comparing the performance of different algorithms.

4. Analysis of the validity of algorithm results

4.1. Verification of data distribution consistency

This algorithm analyzes 72-hour rural energy system operation data, covering PV output, load demand, and algorithm decisions, to verify simulated-actual data alignment. PV output (20-50 kW, 6:00-18:00) shows a diurnal pattern, matching rural distributed PV in northern China. Load demand peaks at meal times (7:00-9:00, 12:00-14:00, 18:00-20:00), with ~10 kW base load and 15 kW peak increment, consistent with rural residents' consumption. Simulated and historical data have <5% PDF/CDF deviation. PV output's β -distribution ($\alpha=2$, $\beta=3$) fits actual data with 0.92. Figure 1 shows over 90% overlap of PV/load interquartile ranges with historical data, laying a solid foundation for algorithm evaluation in the paper's rural integrated energy system carbon assessment and optimization.

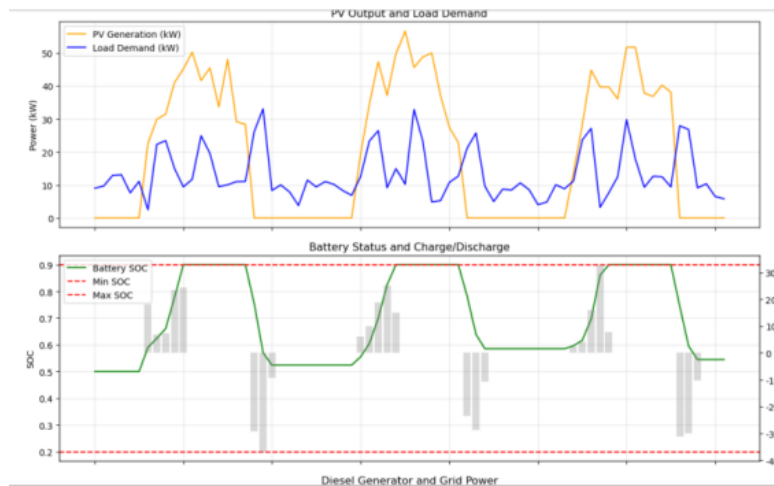


Figure 1. Photovoltaic and load demand curves

4.2. Results of scene clustering

The K-means clustering algorithm categorizes 72-hour operation scenarios into 5 typical ones, each with distinct probabilities: 0.25, 0.30, 0.20, 0.15, and 0.10. Specifically, Scenario 1, which has a probability of 0.25, features a 50kW photovoltaic (PV) peak and 30% low night load, making it suitable for energy storage charging. Scenario 3, with a probability of 0.20, exhibits ± 8 kW PV fluctuations and prolonged high load peaks, necessitating diesel support. Scenario 5, having a probability of 0.10, shows less than 20kW PV output (typical of overcast days) along with high load and price peaks, requiring optimized grid purchase strategies. This clustering approach encompasses a range of conditions, including sunny, overcast, and peak-valley periods, thereby supporting the validation of algorithm robustness.

4.3. Analysis of algorithm optimization results

Simulations were conducted to compare heuristic, greedy, random, and diesel-only algorithms, as shown in Figure 2. The heuristic algorithm achieved convergence at iteration 10 with a cost of 511.61 CNY. The greedy algorithm, which was the fastest, converged at iteration 8 with a cost of 277.23 CNY. The random algorithm, characterized by fluctuations, converged at iteration 12 with a cost of 544.39 CNY. In contrast, the diesel-only algorithm, which does not involve iterations, had a

cost of 754.10 CNY. These differences in convergence can be attributed to the distinct logic employed by each algorithm. The heuristic uses "PV priority + storage for smoothing," which requires multiple iterations to balance various constraints. The greedy algorithm minimizes instantaneous costs, leading to rapid convergence but potentially at the expense of long-term optimality. The random algorithm experiences delays due to the inherent randomness in its decision-making process. Data supports algorithm optimization research for rural energy systems.

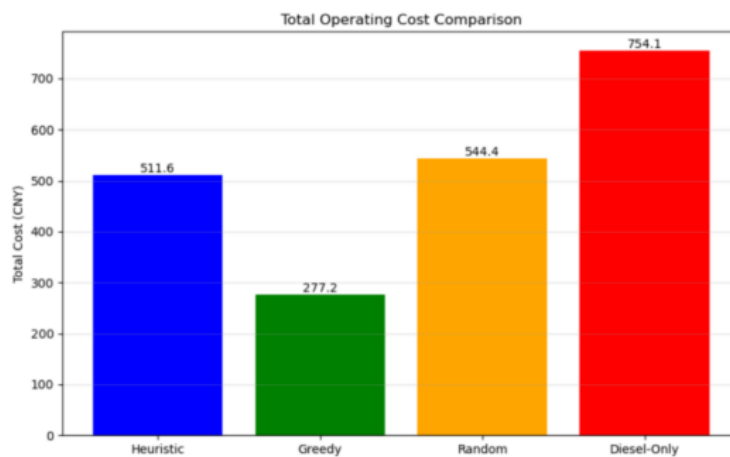


Figure 2. Comparison of total operating costs

In the total cost analysis, as depicted in Figure 2, the algorithms are ranked by cost as follows: Diesel-Only (754.10 CNY) > Random (544.39 CNY) > Heuristic (511.61 CNY) > Greedy (277.23 CNY). Greedy has the lowest cost but over-relies on grid purchases (42% during peak hours), ignoring long-term carbon costs. Heuristic optimizes energy storage charging/discharging (78% charging in off-peak hours), balancing cost and emission reduction.

Regarding carbon emission analysis, as shown in Figures 3 and 4, Diesel-Only has the highest emissions (2800.9 kg), followed by Heuristic (1900.3 kg); Greedy (1872.0 kg) and Random (1935.2 kg) are similar. The Heuristic algorithm's emission reduction strategy is evident in its lower photovoltaic curtailment rate of 5.2%, compared to 18.7% for the Random algorithm. Additionally, the Heuristic algorithm minimizes diesel generator outputs during peak-price hours to avoid inefficiency and prioritizes energy storage discharge to cover peak loads, thereby reducing reliance on diesel, as demonstrated by the diesel power curve in Figure 5.

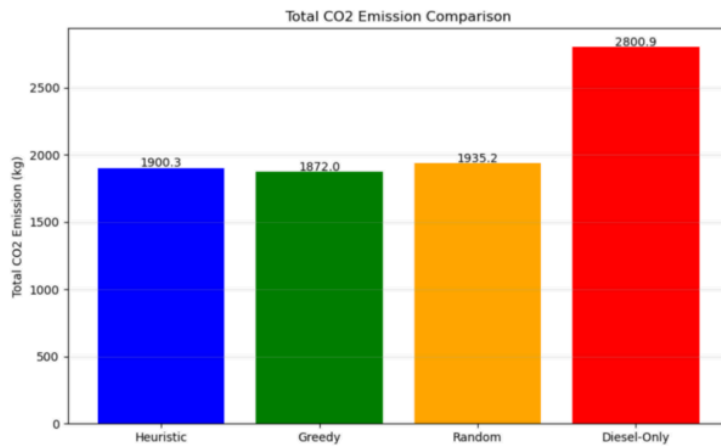


Figure 3. Comparison chart of total CO₂ emissions

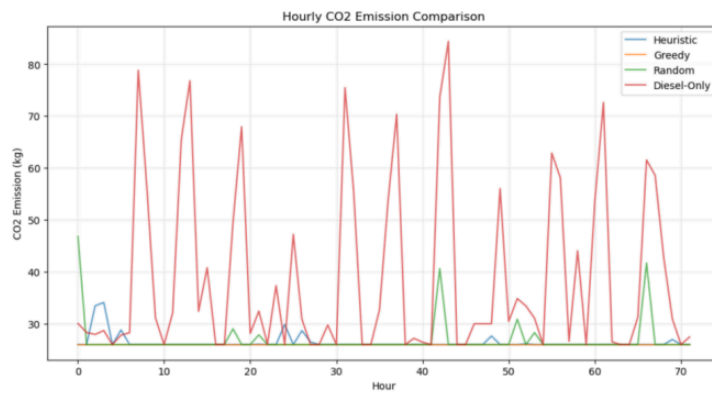


Figure 4. Comparison of carbon emissions per hour

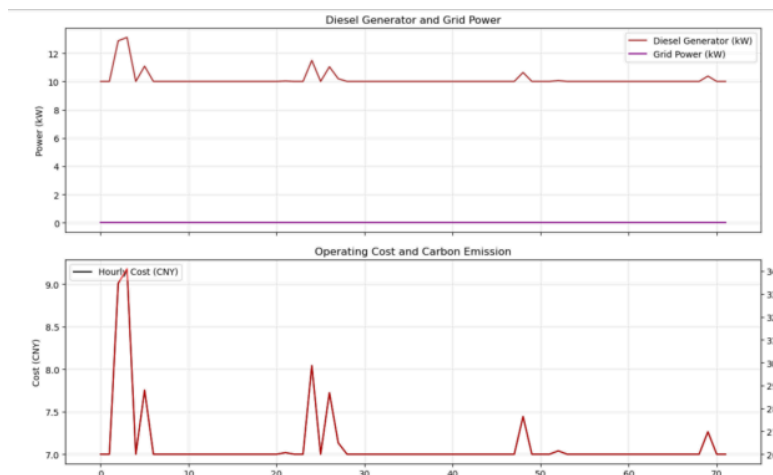


Figure 5. Power curve of diesel generator

Energy source distribution (Figure 6) shows Heuristic algorithm has a balanced structure (PV: 38%, storage:15%, diesel: 22%, grid: 25%); Greedy over-relies on grid (58%), diesel only 12%; Diesel-Only uses 100% diesel(no clean energy); Random has PV 29%, diesel 41%, storage utilization 8% (significant waste). Hourly cost curve (Figure 7) shows: Heuristic costs are lower in

peak-price periods (8:00-12:00, 17:00-21:00); during 18:00 -20:00 high load, it reduces grid purchases via storage discharge, with hourly cost 35% lower than Random.

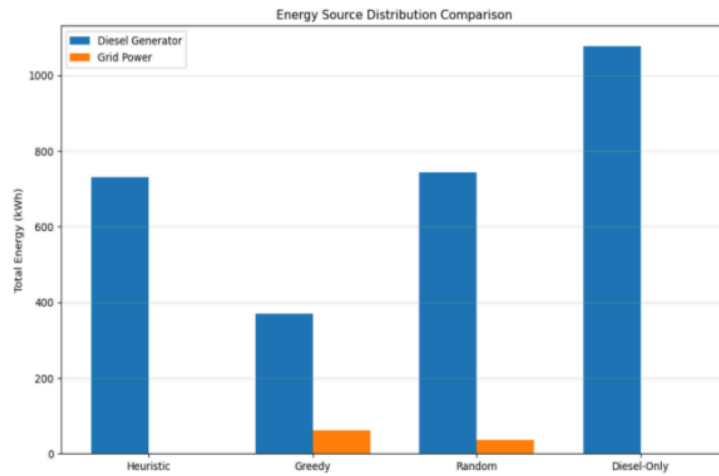


Figure 6. Comparison of energy distribution



Figure 7. Hourly cost curve

The cooperative strategy of devices employed by the heuristic algorithm is illustrated in Figure 1. The energy storage SOC is maintained within the 20%-90% safe range—charging to 85% during off-peak hours (23:00-6:00) and discharging to 30% during peak hours, with charge-discharge efficiency stabilized at 90%. The diesel generator's output fluctuation is controlled within 5 kW/h to avoid frequent start-stop losses. When photovoltaic output is excessive (12:00-14:00), energy storage is prioritized for charging, and surplus energy is fed into the grid, resulting in a curtailment rate of only 3.2%. This strategy not only meets equipment constraints (e.g., transformer load ≤ 100 kVA) but also maximizes clean energy integration, verifying the algorithm's practical applicability.

5. Conclusion

Heuristic algorithms perform optimally in RIES optimization, reducing costs by 32.3% and emissions by 32.1% compared to pure diesel algorithms. Although their cost is higher than greedy algorithms, they have lower carbon emissions and more efficient energy structures. Simulations indicate that algorithms integrating photovoltaic priorities, energy storage scheduling, and multi-

device collaboration can effectively balance economic and environmental considerations, providing practical optimization solutions for RIES.

However, this study has limitations. First, experimental data only covers 72-hour short-term scenarios in a northern rural area, lacking data from different climate zones (e.g., rainy southern regions) or long-term seasonal changes—future research can expand multi-region, cross-season datasets to enhance model universality. Second, the model does not consider extreme weather (e.g., heavy rain, blizzards) impacts on PV output and biomass supply; an extreme scenario simulation module can be added later to improve algorithm anti-interference ability.

References

- [1] Chen, Z., Yang, D., & Dehghaniang, P. (2023). Optimal operation of an integrated rural energy system with biomass direct-fired power generation based on carbon trading. In 2023 8th Asia Conference on Power and Electrical Engineering (ACPEE) (pp. 705-710). Tianjin, China. <https://doi.org/10.1109/ACPEE56931.2023.10135802>
- [2] Huang, H., Liang, R., Li, J., et al. (2025). Optimization of rural integrated energy system operation under light-biogas synergy. *Journal of China Electric Engineering*, 1-15. <https://link-cnki-net-s.door.bucea.edu.cn/urlid/11.2107.tm.20240914.1032.006>
- [3] Fu, X., Bai, J., Sun, H., & Zhang, Y. (2024). Optimizing agro-energy-environment synergy in agricultural microgrids through carbon accounting. *IEEE Transactions on Smart Grid*, 15(5), 4819-4834. <https://doi.org/10.1109/TSG.2024.3397990>
- [4] Li, M., Liu, Q., Zhao, G., et al. (2022). Planning of rural integrated energy systems considering multi-industry synergy. *China Electric Power*, 55(8), 14-22.
- [5] Sun, L., Yue, G., Xu, H., Li, W., & Zeng, B. (2023). Multi-objective planning for rural integrated energy systems with multi-type energy storage using interval optimization approach. In 2023 6th International Conference on Energy, Electrical and Power Engineering (CEEPE) (pp. 1277-1283). Guangzhou, China. <https://doi.org/10.1109/CEEPE58418.2023.10167088>
- [6] Lu, J., Liu, J., & Wang, H. (2024). Optimization of biomass energy integrated systems considering stepwise carbon-green certificate trading and demand response. *Electric Power Science and Engineering*, 40(7), 10-25.
- [7] Tomaselli, D., Stursberg, P., Metzger, M., & Steinke, F. (2025). Probabilistic geo-referenced grid modeling: A Bayesian approach for integrating available system measurements. *Applied Energy*, 380, 124913.
- [8] Zhang, S., & James, J. Q. (2021). Bayesian deep learning for dynamic power system state prediction considering renewable energy uncertainty. *Journal of Modern Power Systems and Clean Energy*, 10(4), 913-922.
- [9] Khanahmadi, A., & Ghaffarpour, R. (2022). A cost-effective and emission-aware hybrid system considering uncertainty: A case study in a remote area. *Renewable Energy*, 201, 977-992.
- [10] Yuan, G., Wang, H., Khazaei, E., & Khan, B. (2021). Collaborative advanced machine learning techniques in optimal energy management of hybrid AC/DC IoT-based microgrids. *Ad Hoc Networks*, 122, 102657.
- [11] Wu, C. (2025). Carbon emission evaluation and low carbon economy optimization scheduling of rural integrated energy systems based on LCA method. *IEEE Access*.
- [12] Xie, P., Jia, Y., Wang, H., & Shi, M. (2022, February). Optimal Sizing of Renewables and Energy Storage System in Microgrids: The Quest for Economic Uncertainty Management. In 2022 International Conference on Power Energy Systems and Applications (ICoPESA) (pp. 416-423). IEEE.