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"Electricity-and-Carbon" Planning for a Residential Solar-Storage Carport

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Abstract. This research develops a lightweight and highly reproducible optimization model for residential solar-storage carport system operating in a carbon-pricing environment. By integrating the real-time carbon price into the system's scheduling decisions, a genetic algorithm is used to simultaneously optimize photovoltaic (PV) and battery storage capacity, as well as the day-ahead dispatch strategy. This optimization framework maximizes electricity export revenues while minimizing total operational costs, including purchased electricity costs, carbon emissions and peak-valley gap penalties. With the current prevalent CO_2 price of 80 RMB/ton, a system configuration with 6.3 kW PV capacity and 5 kW·h/3 kW storage battery achieves an investment payback period of 2.5 years and an internal rate of return of around 40%. Sensitivity analysis reveals that the introduction of a carbon price promotes an increase in electricity sales and improves the financial viability of the system. The results demonstrate that carbon pricing not only increases the economic viability of the system but also promotes more efficient energy use through optimized trading strategies. MATLAB-based template for homes to take part in carbon markets while cutting electricity costs, presenting a route to a more sustainable and economical energy future.

Keywords: Solar-storage carport, Carbon pricing, Rolling optimization, Genetic algorithm

1. Introduction

Climate change necessitates rapid decarbonisation of energy systems. Carbon markets, as market-based mitigation instruments, now transmit hourly price signals that influence the operation of distributed energy resources [1]. Residential photovoltaic-battery (PV-battery) carports have recently become recognised as a central technology for increasing demand-side flexibility and for lowering customer-level greenhouse-gas emissions. Despite this, the planning studies that currently exist for these systems still concentrate mainly on achieving instantaneous power balance and on exploiting electricity-price arbitrage, and they largely ignore the way in which temporal carbon price volatility influences both operational expenditure and day-to-day operating strategies. Consequently, lightweight optimization tools that embed real-time carbon costs remain absent for household applications. To address this gap, the model presents a MATLAB-based electricity–carbon co-optimization model that integrates dynamic carbon pricing into hourly rolling scheduling. The proposed framework turns every goal into one money figure: it cuts the total cash outflow that is made up of the payment for buying electricity, the charge for the carbon this electricity carries, and

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the extra fee that is billed when the gap between the highest and the lowest grid power flow is large, and, at the same moment, it lifts the cash inflow that is received by sending photovoltaic electricity back to the grid. A genetic algorithm determines optimal photovoltaic capacity and battery energy/power ratings, and a model-predictive controller implements day-ahead and real-time dispatch. Numerical results demonstrate that once the carbon-pricing model is introduced, the proposed system becomes profitable, confirming both its economic attractiveness and inherent robustness. The work provides a ready-to-use template that facilitates residential participation in carbon markets.

2. Electricity–carbon co-optimization model for a solar–storage carport

This part introduces the integrated electricity-carbon co-optimization model for a home solar-storage carport. The central idea is explained as follows: buying electricity from the grid brings not only an energy cost but also a carbon cost, determined by the grid carbon emission factor and the real-time carbon price. On the other hand, supplying electricity back to the grid produces revenue and also cancels out the carbon cost. The system structure consists of four main parts: the photovoltaic (PV) unit, the load, the energy storage system, and the connection to the electricity-carbon markets. The mathematical representations for these parts are provided in the subsections below.

2.1. PV model

The photovoltaic component is parameterized using one-hour irradiance records from Beijing, June 2022. A mono-crystalline silicon array is specified with a surface area of 100 m² and a conversion efficiency of 15 %. These parameters define the physical scale and energy-harvesting capability of the system. Under the typical meteorological conditions encoded in the dataset, the array is projected to deliver a rated capacity of 14.18 kW. On an average day it is expected to supply 28.5 kW·h of electrical energy. The final optimized system selects 6.3 kW PV capacity by linearly scaling this 100 m² benchmark profile. The clear-sky output profile of the photovoltaic system is displayed in Figure 1 [2].

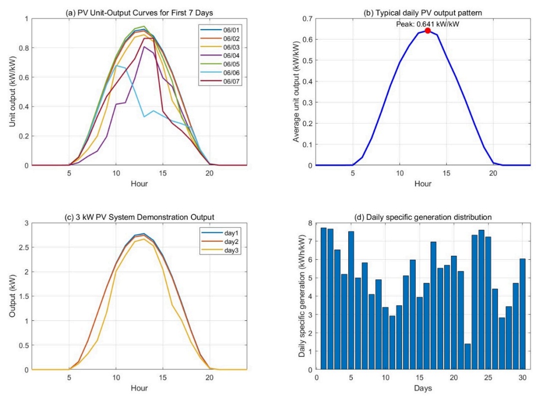

Figure 1. PV output

2.2. Load model

Load is split into work-day and week-end profiles, both shaped with sine curves.

Work-day:

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$$L_{weekday}\,(t) = \begin{cases} 1.5 + 3.5sin\,((t-7)\pi/4), 7 \le t \le 11 \\ 1.5 + 5.0sin\,((t-17)\pi/6), 17 \le t \le 23 \\ 1.5, \;\; otherwise \end{cases} \tag{1}$$

Week-end:

$$L_{weekend}\,(\mathrm{t}) = \begin{cases} 1.5 + 6.0cos\,((t-16)\pi/6), 10 \le t \le 22 \\ 1.5, \;\; otherwise \end{cases} \tag{2}$$

The specific parameters of the sinusoidal functions are configured to produce a final load range of 0-6 kW. To simulate realistic variability, hourly noise of ±15 % and a daily scaling factor between 0.7 and 1.3 are applied. Figure 2 illustrates the typical weekday and weekend load profiles, which are modeled using sine curves to simulate realistic variability.

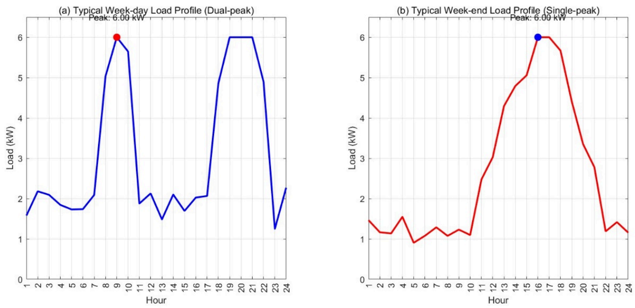

Figure 2. Typical weekday and weekend load profiles

2.3. Carbon price model

The carbon price model is constructed based on a "price shape" concept. Using the 2024 national average carbon price of 80 RMB/ton as a baseline, it is multiplied by a time-of-day step function (0–5 h: 0.8; 6–9 h: 1.0; 10–16 h: 1.2; 17–22 h: 1.0; 23–24 h: 0.8). Random perturbations of ±3% daily and ±5% hourly are superimposed on this profile. This results in a final carbon price range of 63.25–126.57 RMB/ton. The proximity of this range to the projected 2025 national carbon market price (60–80 RMB/ton) supports the plausibility of the model. The baseline carbon price profile, along with random daily and hourly perturbations, is presented in Figure 3.

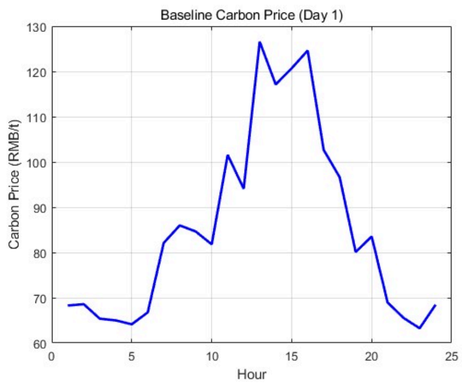

Figure 3. Baseline carbon price

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2.4. Electricity price model

The electricity-price model is built on the 2024 Time-of-Use tariff published for 10 kV industrial users in China [3]. Three tariff tiers are imposed in chronological order. From 0:00 to 8:00 the off-peak rate of 0.35 RMB kW·h^{-1} applies; the standard rate of 0.65 RMB kW·h^{-1} governs the morning and evening blocks, 8:00–12:00 and 18:00–24:00; the midday window, 12:00–18:00, is priced at the peak level of 1.05 RMB kW·h^{-1}. To translate purchased electricity into equivalent carbon dioxide, the simulation adopts the North China grid-average emission factor of 0.9417 kg CO_2 kW·h^{-1}, a value that couples every kilowatt-hour to its indirect emission footprint.

2.5. Energy storage model

The energy-storage unit is a containerized lithium-iron-phosphate (LFP) battery, and its key parameters are summarized in the reference that follows [4]. For modeling purposes, a baseline system with a rated capacity of 25 kW·h and a rated power of 15 kW (corresponding to a 4-hour nominal duration) is defined. The state-of-charge (SOC) is allowed to move only inside the 10 %–95 % window, thereby reserving both a lower safety buffer and an upper margin against over-charge. Energy losses are captured by a round-trip efficiency of 90 %. Power limits, energy-balance dynamics and the daily cycling constraint are expressed analytically as follows:

$$|P_{bat}(t)| \leq 15kW \tag{3}$$

$$E(t+1) = E(t) - P_{bat}(t)/0.9 * \Delta t, \Delta t = 1h \tag{4}$$

$$E(24) = E(0) \tag{5}$$

3. Carbon price-driven rolling optimization algorithm

3.1. Optimization problem formulation

The electricity-carbon co-optimization problem for the solar-storage carport is formulated to minimize the total system operating cost. The core objective function integrates the cost of electricity purchased from the grid, the carbon trading cost, and the revenue from electricity exports. The mathematical expression is given by:

$$minF = C_1 + C_2 + C_3 - C_4 + aC_5 + bC_6 \tag{6}$$

The cost of electricity purchase, charging cost, annualized investment cost, electricity export revenue, carbon emission cost, and peak-valley difference penalty are defined as follows.

$$C_1 = \Sigma_{t=1}^{24} max\left(0, -P_{grid}(t)\right) \cdot \pi_e(t) \tag{7}$$

$$C_2 = \Sigma_{t=1}^{24} P_{load}(t) \cdot \pi_s \tag{8}$$

$$C_3 = r(1+r)^{(Y_{pv})} / \left[(1+r)^{(Y_{pv})} - 1\right] \cdot c_{PV} \cdot A$$

$$+ r(1+r)^{(Y_{bat})} / \left[(1+r)^{(Y_{bat})} - 1\right] \cdot (c_E \cdot E_r + c_p \cdot P_r) \tag{9}$$

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$$C_4 = \Sigma_{t=1}^{24} max\left(0, P_{grid}\left(t\right)\right) \cdot \pi_f \tag{10}$$

$$C_5 = \Sigma_{t=1}^{24} max\left(0, -P_{grid}\left(t\right)\right) \cdot EF_{grid} \cdot \pi_c\left(t\right)/1000 \tag{11}$$

$$C_6 = max_t P_{grid}\left(t\right) - min_t P_{grid}\left(t\right) \tag{12}$$

The weighting coefficients a and b are set to 2 and 1, respectively, to balance the investment cost against the operational penalty in the overall objective. The optimization variables include the photovoltaic capacity PV, the energy storage capacity E_r, and the storage power rating P_r. All solutions are subject to the physical constraints defined in Section 2.5.

3.2. Solution algorithm

The earlier mixed-integer nonlinear programming problem is solved with a genetic algorithm. The calculation process is described as follows:

① Initialization: A group of 50 random capacity setups is produced, where each member includes the three decision variables: [PV, E_r, P_r].

② Fitness evaluation: Calculate the objective function value for each individual. The lower the total cost, the higher the fitness score.

③ Selection: Using the roulette wheel selection method, individuals with high fitness remain in the next generation.

④ Crossover and mutation: Selection of the most suitable individuals involved in crossover operation, which combines two parent solutions into one. Afterwards the whole population goes through an unpredictable mutation procedure to sustain the population variation.

⑤ Termination condition: The iterative process ends when 100 generations are reached or when the solution no longer presents improvements. The optimal capacity configuration is determined as the final result.

After 2,565 fitness evaluations, the genetic algorithm converged to a solution, demonstrating its ability to solve this category of complex optimization problems.

3.3. Uncertainty handling

To handle uncertainties of PV outputs and loads, the historical data-based scenario generation method is adopted in this research [5].

PV Scenario Generation: 30-day PV production data is grouped into four representative output curves using the k-means algorithm. These curves capture typical patterns of energy production under different weather conditions [6].

Load Scenarios: Different baselines are defined for weekdays (bimodal patterns) and weekends (unimodal patterns), respectively. To reflect uncertainties in the future demand scenario, the scaling factor of 0.7–1.3 is uniformly used and Gaussian noise with standard deviation of 15% is added on top of the hourly value.

Scenario probability calculation: based on the data distribution of the past 30 days (22 weekdays and 8 weekend days), the probability of a scenario is set to 73% during weekdays and 27% during weekends.

These probabilities act as input weights for the optimization algorithm.

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3.4. Rolling optimization scheduling strategy

After finding the best capacity setup, the system uses a day-ahead rolling optimization scheduling strategy. This strategy creates a 24-hour optimal charging and discharging plan for the energy storage system using forecasts for the next day, covering solar power generation, charging load, time-of-use electricity prices, and carbon prices.

The scheduling goal is to reduce the total operating cost, defined as the sum of electricity purchase costs and carbon costs, minus the income from electricity sales. The closed-loop character of MPC is achieved by executing only the control actions for the first time step in the optimized sequence; the horizon is then moved one step ahead, the battery SOC and other forecasts are refreshed, and the optimization is run again, forming a continuous feedback-adjustment loop that differs greatly from the one-time schedule of day-ahead static dispatch.

4. Case study validation

4.1. Capacity optimization results analysis

The genetic algorithm effectively reached an optimal setup of 6.3 kW PV and 5 kW·h / 3 kW battery. Working within the limits of a 3kW grid-purchase cap and a 10kW feed-in limit, this setup allows an optimized operation method described as "self-use first, with a small amount of extra electricity returned to the grid."

Economic analysis confirms the strong feasibility of the proposed system. In the baseline carbon price range of 63.25-126.57 RMB/ton, the total annual cost of the system will be 12,053 RMB, of which 248 RMB will be accounted for as carbon cost. The system paid back through the investment within two point five years and the annual operating profit reaches 7,007 RMB [7]. The optimal system capacity configuration and the corresponding annual cost and revenue analyses can be seen in Figure 4.

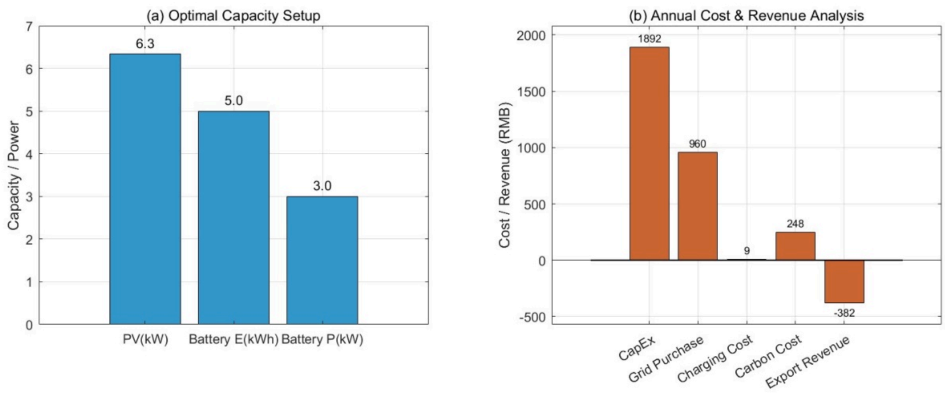

Figure 4. Optimal capacity setup and annual cost & revenue analysis

4.2. Day-ahead scheduling performance evaluation

In the monthly simulations, the operating costs of the plant (including depreciation and amortization costs) are all around RMB 1,058.2 and the daily average of operating cost is about RMB 30.02. Under the carbon price sensitivity analysis, the carbon price directly impacts the operation cost: As the carbon price rises from 0 to 80 RMB/ton, the operating cost rises from 12.74 RMB to 17.61 RMB/daily. The carbon price brings a relative cost rise of 38.2%.

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Moreover, there are certain modifications in the system's electricity trades: the daily purchased electricity grew to 48.98kW·h from 42.35kW·h (a growth of 15.7%), the electric sold increased from 24.22kW·h to 36.57kW·h(an increase of 51.0%), showing that this opposite pattern is made possible by more favorable trading arrangements that can improve energy efficiency constrained by carbon, maximizing profits from exporting power as carbon prices increase. Additionally, charging load optimization reduces the average peak-to-valley load differential by 2.3 kW, and the system exhibits "load-shifting" characteristics that open up additional revenue opportunities through demand response program participation and grid services [8].

Even with higher operational costs under carbon pricing, the project stays economically feasible through improved energy management. The large rise in electricity sales income partly makes up for the carbon cost load, showing the system's ability to handle environmental policy changes. Figure 5 provides a heat-map of the PV and grid power generation, emphasizing the system's performance during the 30-day simulation, while Figure 6 gives the daily total cost breakdown with different cost.

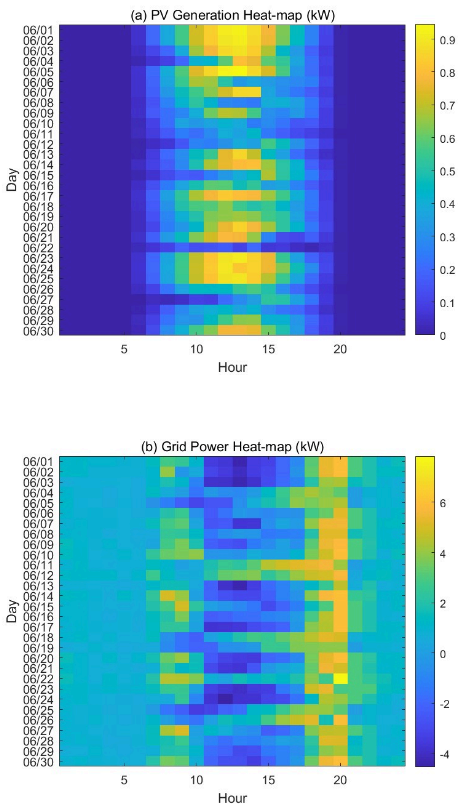

Figure 5. PV and grid power generation heat-map

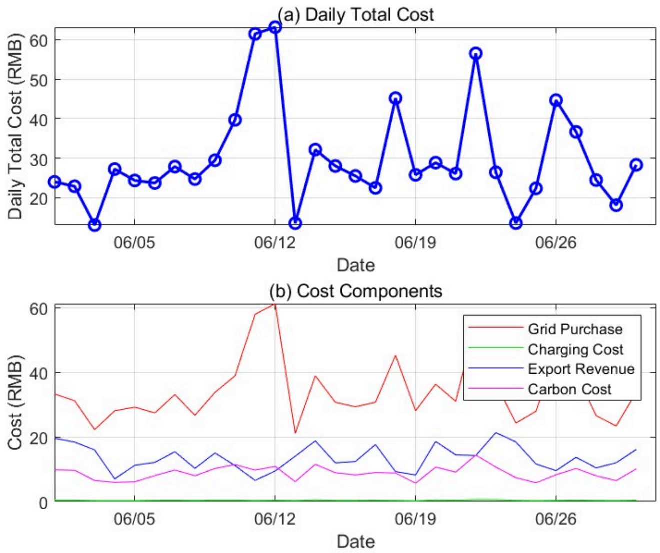

Figure 6. Daily total cost and breakdown of cost components

5. Conclusion

This paper introduces a complete electricity-carbon co-optimization framework for residential solar-storage carport systems. Through systematic modeling and simulation, an optimal configuration consisting of 6.3 kW PV and 5 kW·h/3 kW battery was established and confirmed to have robust economics and operational performance under fluctuating carbon pricing regimes.

The simulation results confirm the economic viability of the system, with a total annual cost of approximately 12,053 RMB. a payback period of 2.5 years, and a rate of return equivalent to 40% per year. Of particular importance is the magnitude of the impact that carbon prices have on the system economy. When the carbon price moves from 0 RMB/ton to 80 RMB/ton, the system's total daily operation cost changes from 12.74 RMB to 17.61 RMB, which means that there is an increase rate of 38.2%, directly related to internalizing carbon cost into the electric cost.

The system manifests its adaptable operational activities towards carbon signals, with analysis exhibiting an increase in daily procurement of electricity from 42.35 kW·h to 48.98 kW·h, together with greater electricity sold from 24.22 kW·h to 36.57 kW·h. It conveys better energy efficiency gains under carbon pressure. Also, the proposed approach enables grid service provision through lowering the peak-valley load difference from 2.3 kW, thus being endowed with "load-shifting" capability and enabling participation of demand response.

A key output of this work is an effective and completely repeatable approach to creating a MATLAB-based optimization template for the home-energy system sector (home solar, storage, and charging) that allows individual home energy systems to be optimized for participation in the carbon market. This framework for integrated electricity-carbon optimization is critical for transitioning home energy systems from passive consumers to active market participants.

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