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Research on the Benefits of UAVs for Offshore Wind Farm O&M—Analysis Based on the UAV D-LCOE Model

Peng Wenquan[1,a], Lu Zhi[1,b], Huang Yaokun[1,c], Zheng Kai[1,d], Huang Siling[1,e], Zheng Wenjing[1,f], Zhao Guorui[1,*,g]

[1]*School of Computer Science and Engineering, Guangdong Ocean University, Yangjiang, China*
[a]*15622808251@stu.edu.gdou.cn,* [b]*13825651778@163.com,* [c]*13926425413@stu.gdou.edu.cn,*
[d]*15013168099@stu.gdou.edu.cn,* [e]*15816971598@stu.gdou.edu.cn,* [f]*202344011236@stu.gdou.edu.cn,*
[g]*zhaoguoruimath@foxmail.com*
[*]*Corresponding author*

Abstract: *This study innovatively develops a UAV D-LCOE model to quantify the cost reduction of UAV-based operation and maintenance (O&M) for offshore wind farms, using the UK Round 3 project as a case. Analysis shows that UAV O&M, through automated inspection and swarm coordination, significantly lowers costs, reducing the levelized cost of energy (LCOE) by 28% and achieving cumulative savings of ¥120 million. Empirical findings identify swarm efficiency gains (47% in 15-point scenarios) and an average annual equipment learning rate of 7.2% as the core drivers. The study provides a practical quantitative tool and decision support for optimizing offshore wind O&M costs.*

Keywords: *offshore wind power; UAV operations and maintenance; levelized cost of energy (LCOE); cost optimization; UAV D-LCOE model*

1. Introduction

The levelized cost of energy (LCOE) [1] represents the unit cost of electricity generation, calculated by discounting total lifecycle costs and generation over a project's lifetime at an appropriate discount rate. When LCOE falls below market electricity prices, the project becomes economically viable. Offshore wind farm operations and maintenance (O&M) confront challenges including technological innovation barriers and extended payback periods for cost and emission reductions. Addressing these requires lowering labor costs and minimizing failure risks to enhance returns and reduce losses, underscoring the value of research into related technological innovations. To enhance LCOE model accuracy, this paper adopts dynamic discount rates over static ones, as static rates fail to capture evolving financial risks and the time value of money, potentially introducing bias. The Nelson-Siegel model [2] , widely used in economics to derive future discount rates from current yield curves, enables this dynamization.

Traditional manual O&M suffers from hazards, time consumption, and high costs. Technological advances have popularized unmanned aerial vehicles (UAVs) for infrastructure inspection and maintenance. For extensive wind farms, multi-UAV collaborative O&M is essential, posing complex operations research optimization challenges. Scholars have explored UAV swarm inspection path optimization [3-5], establishing foundations for collaborative efficiency gains. However, studies integrating UAV economic benefits—such as labor replacement—into full lifecycle levelized analyses remain limited.

This paper examines UAV economic benefits for offshore wind farm O&M. By incorporating the Nelson-Siegel model for dynamic LCOE discounting, we develop a full lifecycle cost model integrating carbon pricing, establish a quantitative techno-economic framework for UAV O&M, and create a UAV D-LCOE system linking "equipment-environment-carbon market" factors. The goal is to quantify UAV economic contributions and provide dynamic predictions and decision support for O&M cost optimization.

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2. Materials and Data

The installed capacity data for the three phases of the Guangdong Yuedian Zhanjiang Wailuo Offshore Wind Farm are sourced from Guangdong Yuedian Qujie Wind Power Co., Ltd. Chinese government bond interest rates are sourced from the Ministry of Finance of the People's Republic of China [6].Chinese carbon trading price data are sourced from the Shanghai Environment and Energy Exchange . Unit investment cost data for each phase of the Guangdong Yuedian Zhanjiang Wailuo Offshore Wind Farm are sourced from Guangdong Electric Power Development Co., Ltd. [7] . Initial generation data for each phase can be found in references [8, 9] . UAV inspection distance data can be found in references [10, 11] . The inspection distances are estimated based on the offshore distances of each phase. Phase I covers approximately 29 km², with the nearest point 10.5 km and the farthest 17.5 km from shore, yielding an estimated inspection distance of about 30 km. Phase II ranges from 15 km to approximately 20 km from shore, yielding an estimated inspection distance of 38 km. Phase III covers approximately 38 km², ranging from 10–16 km from shore. Given its significantly larger sea area than Phase I, the estimated inspection distance is 45 km. Other data are averaged from market sources. The data are shown in the following table:

Table 1 Parameters of the Guangdong Yuedian Zhanjiang Wailuo Offshore Wind Farm.

Parameter Name	**Symbol**	**Parameter Name**	**Symbol**
O&M vessel daily rental cost (yuan/day)	c_ship	UAV operating cost (yuan/hour)	c_drone
O&M vessel rental days (days/year)	t_ship	UAV flight time (hours)	t_flight
Technician daily salary (yuan)	c_crew	UAV inspection downtime (hours)	t_downtime_UAV
Technician deployment days (days/year)	t_crew	Number of wind turbines (units)	N_turbines
Loss per hour during downtime (yuan/hour)	c_downtime	Annual inspection frequency (times/year)	f_inspection
Manual inspection downtime (hours)	t_downtime	Unit investment cost for phase p (yuan/kW)	Ip
Installed capacity for phase p	Qp	UAV inspection distance for phase p	Lp
UAV inspection distance for phase p	Lp	Initial generation for phase p	Ep
Maximum carbon price in year t	Pcap,t	Minimum carbon price in year t	Pbase,t
Short-term interest rate for phase p	K1,p	Medium-term interest rate for phase p	K2,p
Long-term interest rate for phase p	K3,p		

3. LCOE Cost Model Based on Intelligent UAV O&M Optimization

3.1 Total Lifecycle Investment Cost Present Value Model

The main investment cost in an offshore wind farm is for the installation of wind turbines.

Let the actual newly installed capacity of phase p be Q_p, the actual cumulative installed capacity of phase p be $Q_{sum,p}$, and the ideal cumulative installed capacity of phase p be Q_{ref} Then $Q_{sum,p}$ can be obtained by summing the actual newly installed capacity Q_p of phase p, calculated as follows:

$$Q_{sum,p} = \sum_{k=0}^{p} Q_k \tag{1}$$

Let the technical learning efficiency be b, and the learning rate under ideal production ($Q_{sum,p} = Q_{ref}$) be λ. The technical learning rate LR is calculated as follows[12]:

$$LR = 1 - (\frac{Q_{sum,p}}{Q_{ref}})^{-b} \tag{2}$$

where the ideal learning rate is calculated by substituting the data for each phase into $LR = 1 - (\frac{Q_{sum,p}}{Q_{ref}})^{-b}$, taking the maximum value of LR.

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Let the base investment cost be I_{base} , and the investment cost in year t be I_t. Based on Wright's Law [13] , wind power installation costs decrease as cumulative production increases. This study constructs a dynamic learning rate model, where the investment cost I_t in year t can be expressed as:

$$I_t = I_{base} \cdot (1 - LR) \tag{3}$$

3.2 Dynamic Discount Rate Model

To improve model accuracy, the Nelson-Siegel model is used to dynamically fit the government bond yield curve over the years, and a carbon emission cost policy factor is introduced to jointly construct the dynamic discount rate r_t.

Let the discount rate in year to be r_t, the interest rate of long−term bonds be β_0, the difference between the interest rate of short−term bonds and that of long−term bonds be β_1, the curvature of the medium−term bond interest rate curve over the term be β_2 , and the decay rate factor of the influence of short-term bond interest rates on long-term bond interest rates in year t be λ_t . Based on the Nelson-Siegel interest rate expectation structure model, β_0 is the long-term interest rate level, β_1 is the difference between short-term and long-term interest rates, β_2 is the medium-term interest rate curvature, and the decay rate in year t is λ_t. The impact factor of government bond interest rates on the discount rate r in year t is established as:

$$\beta_0 + \beta_1 \cdot \frac{1-e^{-\lambda_t}}{\lambda_t} + \beta_2 \cdot \left(\frac{1-e^{-\lambda_t}}{\lambda_t} - e^{-\lambda_t}\right) \tag{4}$$

Energy production inevitably generates carbon emissions directly or indirectly. For model generalization, only the floor and ceiling prices per ton of carbon are set during modeling, with a policy adjustment factor added to the floor price. Each year, the maximum value between the adjusted price for that year and the maximum interval pricing is taken as the price paid by enterprises for emitting one ton of carbon.

Let the initial year be t_0 , the government's maximum interval pricing for one ton of carbon emissions in year t be $P_{cap,t}$, the floor price be $P_{base,t}$, and the growth rate of the floor price in year t be k_t. The cost $P_{carbon}(t)$ for one ton of carbon emissions in year t is calculated as follows:

$$P_{carbon}(t) = Max\left(P_{base,t} \cdot e^{k(t-t_0)}, P_{cap,t}\right) \tag{5}$$

Let the increase in the discount rate due to market volatility in year to be ε_t, and the increase in the discount rate due to carbon emission cost increases in year t beγ_t. The initial discount rate is r_0. The impact factor of carbon emission policies and market volatility on r in year t is calculated as follows:

$$r_0 + \gamma_t \cdot P_{carbon}(t) + \varepsilon_t \tag{6}$$

Combining equations (4), (5), and (6), the dynamic discount rate model is obtained:

$$r_t = r_0 + \beta_0 + \beta_1 \cdot \frac{1-e^{-\lambda_t}}{\lambda_t} + \beta_2 \cdot \left(\frac{1-e^{-\lambda_t}}{\lambda_t} - e^{-\lambda_t}\right) + \gamma_t \cdot P_{carbon}(t) + \varepsilon_t \tag{7}$$

3.3 Total Lifecycle Generation Present Value

Throughout the full lifecycle of wind power equipment generation, mechanical work efficiency decreases due to equipment aging and environmental corrosion, so the production process must account for capacity reduction caused by these factors.

Let the annual degree of mechanical aging be δ_{mech}, the degree of environmental corrosion be $\delta_{env}$and the year when mechanical aging and environmental corrosion begin to have a non-negligible impact on machine work efficiency be $t_{threshold}$. Let the decay rate of energy degradation caused by environmental corrosion and equipment aging in year t be δ_t, δ_t is calculated as follows:

$$\delta_t = \delta_{mech} + \delta_{env} \cdot Max(0, t - t_{threshold}) \tag{8}$$

The cumulative degradation model is a degradation modeling method based on probabilistic statistics, primarily used to predict the nonlinear degradation pattern of equipment performance over time. The process by which wind power equipment performance declines year by year, leading to capacity reduction, aligns with the cumulative degradation model [9]. Let the initial generation be E_o and the generation in year t be E_t. Based on the cumulative degradation model and combining equation (8), the total lifecycle generation present value model is established:

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$$E_t = E_o \cdot \prod_{k=1}^{t}(1-\delta_k) \tag{9}$$

3.4 Dynamic UAV O&M Cost Model

To quantify the reduction in O&M costs brought by the UAV system, let the initial O&M cost be O_{base}, the annual efficiency gain from technological progress for UAV O&M be η, and the generation gain from UAV O&M be α_{drones}. The UAV O&M cost in year t is calculated as follows:

$$O_t = O_{base} \cdot (1-\eta)^t \tag{10}$$

LCOE is calculated as the present value of total costs divided by the present value of total generation. Combining equations (3), (7), and (10), the dynamic LCOE cost model based on intelligent UAV O&M (UAV Dynamic Levelized Cost of Energy, abbreviated as UAV D-LCOE) is constructed as follows:

$$LCOE = \frac{\sum_{t=0}^{T} \frac{I_t + O_t + P_{carbon}(t)}{(1+r_t)^t}}{\sum_{t=0}^{T} \frac{E_t}{(1+r_t)^t}} \tag{11}$$

3.5 UAV O&M Cost Efficiency Model

After introducing UAVs for fully automated O&M, enterprises can reduce labor costs, O&M vessel rental, downtime duration, and working hours. The following sections establish a UAV O&M cost efficiency model to compare the annual cost difference between manual O&M and UAV O&M.

Let the daily rental cost of an O&M vessel be c_{ship} yuan, the number of days required to rent an O&M vessel for one task be t_{ship}, the daily salary of a technician be c_{crew} yuan, the number of days each technician needs to invest per task be t_{crew}, the loss per hour during downtime be $c_{downtime}$ yuan, and the downtime caused by one manual inspection task be $t_{downtime}$. The traditional manual O&M cost is calculated as:

$$C_{manual} = c_{ship} \times t_{ship} + c_{crew} \times t_{crew} + c_{downtime} \times t_{downtime} \tag{12}$$

UAV system O&M needs to account for flight costs and downtime losses. Let the O&M cost of using one UAV be c_{drone} yuan/hour, the flight time required for a UAV to inspect a group of wind turbines be t_{flight} hours, and the downtime caused by UAV inspection be $t_{downtime\_UAV}$ hours. The UAV O&M cost is calculated as:

$$C_{UAV} = c_{drone} \times t_{flight} + c_{downtime} \times t_{downtime\_UAV} \tag{13}$$

3.6 Collaborative Efficiency Gain Model

For O&M operations, the most important consideration is the time required for each operation. UAV O&M can be divided into single-UAV and multi-UAV operations based on the number of devices. The following presents the mathematical assumptions and model calculation process for UAV time consumption.

Let the flight length of the UAV swarm on segment i be L_i meters, the average cruising speed of the UAV swarm be v m/s, the time for a single UAV to hover and photograph at each point be $t_{hours,single}$ seconds, and the total number of inspection points be n_{points}. The time for UAVs to inspect region i is:

$$f(x_i)\frac{L_i}{v} + t_{hours,single} \times n_{points} \tag{14}$$

The total duration formulas for swarm inspection and single-UAV inspection are respectively:

$$T_{multi} = \max(f(x_1), f(x_2) \dots \dots f(x_n)) \tag{15}$$

$$T_{single} = \sum_{i=1}^{n} \mathrm{f}(x_i) \tag{16}$$

Combining equations (14) and (15) to quantify the time benefit of multi-UAV O&M compared to single-UAV O&M, the collaborative efficiency gain model is obtained as:

$$\eta_{muti} = \frac{T_{multi}}{T_{single}} \tag{17}$$

Combining equations (13) and (16), the total cost formula for wind farm O&M using a swarm is:

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$$C_{UAV\_muti} = c_{drone} \times t_{flight} \times \eta_{muti} + c_{downtime} \times t_{downtime\_UAV} \tag{18}$$

By comparing traditional manual O&M costs and UAV O&M costs, the annual cost savings can be obtained. Let the current wind farm have $N_{turbines}$ wind turbines, and $f_{inspection}$ inspection operations be required per year. The annual cost savings formula is:

$$\Delta C = \left(C_{manual} - C_{UAV\_muti}\right) \times N_{turbines} \times f_{inspection} \tag{19}$$

Combining equations (11) and (18), the levelized cost of energy formula after introducing the UAV O&M system is:

$$LCOE = \frac{\sum_{t=0}^{T} \frac{I_t + O_t + P_{carbon}(t) - \Delta C}{(1+r_t)^t}}{\sum_{t=0}^{T} \frac{E_t}{(1+r_t)^t}} \tag{20}$$

4. Results Analysis

Based on an 8-year lifecycle, 100 turbines, and 5 inspections per year, the model calculates a levelized cost of energy (LCOE) of 0.1439 yuan/kWh. This cost remains stable throughout the project, reflecting the model's effective balance after comprehensively considering discount rates, equipment degradation, technological progress, and various cost factors.

Traditional manual O&M costs are 42,988 yuan per operation, while UAV O&M costs are significantly lower: 162 yuan per operation for the single-UAV solution, and further reduced to 67 yuan per operation for the multi-UAV collaborative solution. This difference primarily stems from the UAV solution saving labor, vessel rental, and downtime losses. Multi-UAV collaboration improves efficiency through path optimization and task allocation. Under this configuration, total annual costs can be saved by approximately 21.46 million yuan.

The multi-UAV collaborative efficiency coefficient is 0.411, meaning a time efficiency improvement of approximately 58.9% compared to single-UAV operations. This is mainly due to parallel operations of multiple UAVs, path optimization, and collaborative control, which shorten overall operation time through task decomposition and resource sharing, thereby reducing direct costs and downtime losses. This is a key factor in improving O&M economics.

The learning rate curve in Figure 1 shows that the learning rate is negative in the first 5 years and gradually converges to zero, corresponding to learning costs from initial technology deployment and debugging. After year 5, it becomes positive and rises rapidly, reflecting the cost reduction effect from technology maturity and experience accumulation. This trend aligns with Wright's Law, indicating that technological progress in later stages has a positive impact on reducing LCOE.

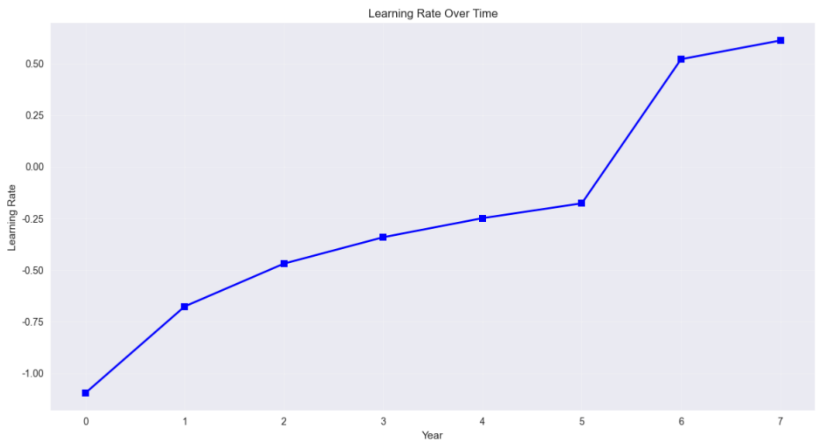

Figure 1 Learning Rate Variation Over Time.

The equipment degradation rate curve in Figure 2 shows that in the first 5 years (t<$t_{threshold}$), the degradation rate remains constant at 0.005, which is consistent with the model assumption that the impact of mechanical aging and environmental corrosion on efficiency is negligible before reaching the threshold year. Starting from year 6, the degradation rate jumps to 0.008, and further increases to 0.011 in year 7, reflecting the accumulation and acceleration of equipment aging effects.

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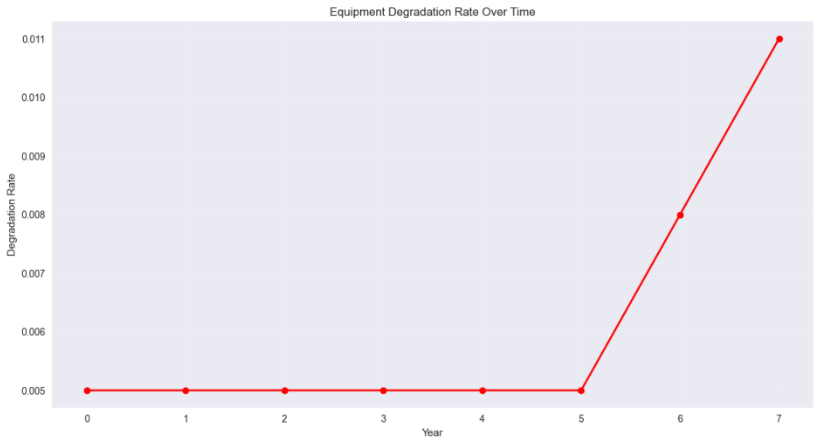

Figure 2 Equipment Degradation Rate Over Time

Figure 3 shows that generation gradually decreases from an initial 990,000 kWh to 950,000 kWh, primarily due to equipment degradation and environmental factors. Notably, in later stages (years 5–7), installed capacity grows from near zero to approximately 39,000 MW, but generation does not increase proportionally, indicating that new capacity is still under construction and commissioning or offset by efficiency losses. This suggests that evaluating wind power projects requires comprehensive consideration of multiple factors, including actual generation efficiency, equipment degradation, and grid connection time.

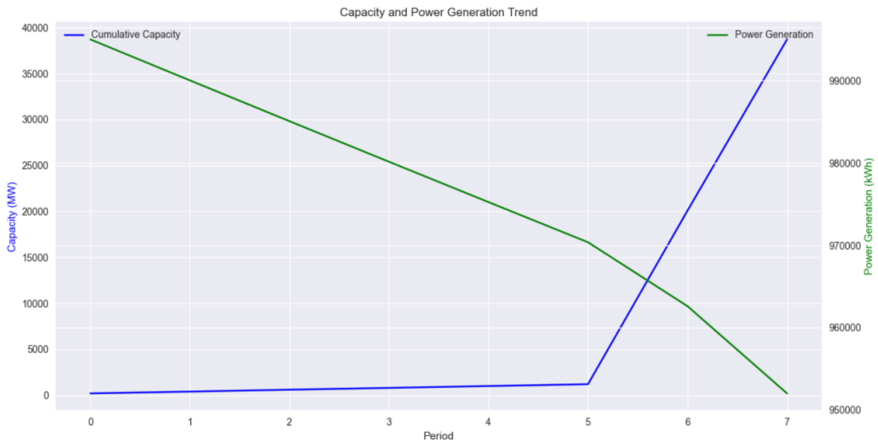

Figure 3 Capacity and Generation Trend.

The study reveals that cumulative installed capacity growth exhibits distinct phases—slow initial expansion followed by rapid increases—reflecting progression from project preparation to concentrated construction, with complex effects on LCOE: later-stage concentrated investments benefit cost reduction through discounting effects, yet lag in generation revenue extends payback periods, while dynamic cost balances maintain LCOE stability. Intelligent UAV O&M significantly reduces wind power project LCOE, with multi-UAV collaborative solutions cutting per-operation costs from 42,988 yuan to 67 yuan (a 99.8% reduction) and yielding annual savings exceeding 21 million yuan through reduced O&M expenditures and downtime, amplifying advantages for large-scale farms. However, based on specific model assumptions, practical applications require consideration of regional, technological, and policy factors; future research should calibrate parameters with operational data, explore scenario-specific cost-effectiveness, and investigate issues like extreme weather reliability, data security, and hybrid O&M strategies.

5. Research Conclusions

This study systematically analyzes the economics of wind farm projects using an LCOE model optimized for intelligent UAV O&M. The UAV solution shows significant cost advantages: under given configurations, multi-UAV collaboration cuts per-operation costs from 42,988 yuan to 67 yuan (a 99.8% reduction), yielding annual savings exceeding 21 million yuan due mainly to reductions in labor, vessel

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rental, and downtime. With an efficiency coefficient of 0.411 through parallel operations and path optimization, time efficiency improves by 58.9%, and cost savings scale with project size. Technological progress and learning curves notably affect LCOE, where early negative rates reflect initial costs, followed by positive improvements as technology matures, aligning with Wright's Law. A dynamic balance between equipment degradation and capacity growth is key to LCOE stability, requiring integrated evaluation of efficiency, degradation, and grid connection timing. The model yields a stable lifecycle LCOE of 0.1439 yuan/kWh, demonstrating its capability to balance dynamic cost factors.

Methodologically, this study innovatively integrates full lifecycle costing, dynamic discounting, carbon pricing, equipment degradation, and multi-UAV efficiency into a coherent analytical framework that accounts for time value, technological progress, and environmental costs. It offers a new tool for quantifying UAV swarm O&M economics and can be extended to other energy infrastructure requiring regular inspection. Limitations include reliance on theoretical parameters needing field calibration, idealized assumptions that should incorporate regional, weather, and policy variables, and insufficient coverage of practical issues such as data security and hybrid strategies.

Future research should focus on parameter calibration with real operational data, cost-effectiveness analysis across scenarios, long-term technology impact, reliability in extreme weather, hybrid O&M strategies, model extension to other renewables, and inclusion of environmental and social benefits for a more comprehensive assessment. In summary, this study systematically outlines the economic advantages and mechanisms of UAV O&M solutions, supports intelligent O&M adoption decisions, and contributes new theoretical and methodological tools to energy project lifecycle assessment. As UAV technology matures and costs decline, it is expected to become a mainstream approach for enhancing renewable energy sustainability.

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References

[1] SHORT W, PACKEY D J, HOLT T. A manual for the economic evaluation of energy efficiency and renewable energy technologies[J]. NASA STI/Recon Technical Report N, 1995, 95

[2] NELSON C R, SIEGEL A F. Parsimonious Modeling of Yield Curves[J]. The Journal of Business, 1987, 60(4): 473–489.

[3] XU L, CAO X, DU W, et al. Cooperative path planning optimization for multiple UAVs with communication constraints[J]. Knowledge-Based Systems, 2023, 260: 110164.

[4] ISMAIL A H, SONG X, OUELHADJ D, et al. Unmanned surface vessel routing and unmanned aerial vehicle swarm scheduling for off-shore wind turbine blade inspection[J]. Expert Systems with Applications, 2025, 284: 127534.

[5] ZHEN L, YANG Z, LAPORTE G, et al. Unmanned Aerial Vehicle Inspection Routing and Scheduling for Engineering Management[J]. Engineering, 2024, 36: 223–239.

[6] Ministry of Finance of the People's Republic of China. Official Website of the Ministry of Finance of the People's Republic of China [Z]. Ministry of Finance of the People's Republic of China. 2025.

[7] Board of Directors of Guangdong Electric Power Development Co., Ltd. Guangdong Electric Power Development Co., Ltd. (Yuedianli A): Announcement on Investing in the Construction of the Zhanjiang Wailuo Offshore Wind Power Project (Phase I) [Z]. Sina Finance (stock.finance.sina.com.cn). 2018.

[8] Southern+ (Platform). Guangdong Energy Group's Zhanjiang Wailuo Offshore Wind Power Phase III Project Achieves Full Capacity Grid Connection [Z]. Southern+ (southcn.com). 2021.

[9] China Communications Construction Company First Harbor Engineering Co., Ltd. (Source). Completion of Guangdong's First Large-Megawatt Offshore Wind Power Project (Guangdong Yuedian Zhanjiang Wailuo Offshore Wind Power Project Phase I) [Z]. China Communications Construction News Network (cccnews.cn). 2019.

ISSN 2616-5775 Vol. 9, Issue 2: 46-53, DOI: 10.25236/AJCIS.2026.090207

[10] Guangdong Yuedian Qujie Wind Power Co., Ltd. (Tenderer), Guangdong Far East Tendering Agency Co., Ltd. (Tendering Agency). Wailuo Phase I and Phase III Offshore Wind Farm Offshore Substation Foundation Anti-8Scour Research and Treatment Project (Tender Announcement) [Z]. Guangdong Far East Tendering Agency Official Website (gdydzb.com). 2024.
[11] Electric Wind Power (Information Source). First Batch of Wind Turbines Successfully Connected to the Grid in Zhanjiang Wailuo Offshore Wind Power Project Phase II [Z]. Polar Power News Network (bjx.com.cn). 2021.
[12] NAGY B, FARMER J D, BUI Q M, et al. Statistical basis for predicting technological progress[J]. PLoS One, 2013, 8(2): e52669.
[13] WRIGHT T P. Factors affecting the cost of airplanes[J]. Journal of the Aeronautical Sciences, 1936, 3: 122–128.