

Article

A Dynamic Penetration-Rate-Driven Analytical Framework for Offshore Wind–Green Hydrogen Hybrid Systems

Linghe Ye and Lin Lu *

Department of Building Environment and Energy Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong SAR 999077, China; tristan.ye@connect.polyu.hk

* Correspondence: vivien.lu@polyu.edu.hk; Tel.: +852-3400-3596

Abstract

To analyze the impact of the expansion of grid connections for renewable energy sources, such as offshore wind power, and the application of energy storage technologies, such as hydrogen energy storage, on the energy system, this paper develops a dynamic penetration-rate-driven analytical framework (DPRAF). It analyzes the impact of relevant factors on the dynamic renewable energy penetration rate, changes in energy structure, electricity prices, and environmental governance costs. An improved two-stage optimization process comprising planning and verification is used to obtain system schemes and hourly penetration rates across various scenarios. The study found that the scale of wind power grid connection has a significant impact, while the application of hydrogen energy storage technology has a cumulative effect. This article also clarifies the transmission mechanism of the impact of renewable energy grid connection on market electricity prices in an imperfectly competitive market environment. Every 8 GW increase in grid-connected offshore wind capacity results in a rise of approximately HKD 0.004 per kWh in the electricity price under peak-time mode. The 16–24 GW range is viewed as a pragmatic compromise zone where the benefits of emission reduction remain commensurate with the associated environmental costs; however, once installed capacity exceeds 24 GW, electricity prices and the burden of mitigation measures experience a sharp, non-linear surge. The increase in grid connection scale will widen the environmental governance cost gap between liquefied hydrogen storage solutions and other solutions. The findings of this study further highlight the necessity of balancing benefits and overall costs in the development and application of renewable energy, providing a reference for future related work.

Keywords: offshore wind power; electricity tariff; penetration rate; environmental governance cost

Academic Editor: Carlos Vargas-Salgado

Received: 3 July 2026
Revised: 28 July 2026
Accepted: 30 July 2026
Published: 3 August 2026

Copyright: © 2026 by the author. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\) license](https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The intensifying greenhouse effect and a deteriorating global security landscape are compelling nations to expand the role of renewable energy sources (RE) to pursue environmental benefits and energy independence. Yet greater RE penetration introduces supply instability, price volatility, and heightened backup capacity requirements [1,2]. To capture the evolution of this transformation, this study focuses on dynamic renewable energy penetration based on the previous work, defined as the ratio of real-time renewable energy grid supply to grid demand [3,4]. Unlike the static proportion of RE installed capacity, this indicator more clearly reflects the impact of investment decisions and technological

constraints. Crucially, changes in this dynamic RE penetration rate directly affect core dimensions of energy security—including reliability, resilience, and sustainability—and reshape electricity pricing mechanisms amid market concentration and regulatory intervention [5–7]. Therefore, clarifying how specific variables, such as wind power capacity and hydrogen storage deployment, affect this dynamic penetration rate, as well as their downstream economic and environmental consequences, is of great significance for RE applications and energy development.

Previous studies have provided extensive discussions on the mechanism underlying the dynamic RE penetration rate. One significant perspective is the analysis of the impact of technological factors, including the mechanism by which overall system efficiency and security factors shape the dynamic RE penetration rate. Many studies have shown that the development and deployment of energy storage systems, grid technologies, and control strategies positively impact system flexibility and the integration capacity of renewable energy [8–11]. Other noteworthy technological factors include system optimization, distributed systems, and the application of artificial intelligence and machine learning [12–15]. The key technical elements of previous research work have been compared in Table 1. However, most current studies generally treat the dynamic renewable energy penetration rate as a feedback loop, neglecting its further impact on the overall energy system as a driving variable, and lacking quantitative analysis of this mechanism. These research directions urgently require corresponding research.

Beyond the physical and technical aspects, analogous gaps exist in economics and environmental policy, where related factors operate through a complex mechanism of mutual influence, as has been well demonstrated in previous studies. Existing analyses of economic and policy factors focus on the decision-making elements on the investment side, including investment strategies [16,17], development costs [18,19], and policy guidance [19–22], while also accounting for the impact of energy consumption. In addition, some comprehensive perspectives have revealed the complex mechanisms involved [23,24]. However, research on the driving effects of dynamic RE penetration rates remains insufficient. Existing studies have also failed to fully consider the unique characteristics of pricing mechanisms in energy markets with strong regulation and regional monopolies, requiring further analysis.

To address the limitations of existing research, this study constructs an analytical framework based on dynamic penetration rates (DPRAF). A key feature of this framework is the treatment of the dynamic penetration rate of renewable energy as a core operational indicator, thereby directly reflecting real-time changes in the structure of energy production and consumption. Driven by this high-frequency structural feedback, the framework quantifies how renewable energy grid integration and energy storage deployment, within the context of a highly regulated monopoly regime, which influences electricity prices and environmental governance costs through a series of downstream transmission mechanisms.

Existing research has explored renewable integration from various perspectives. Techno-economic assessments typically focus on levelized costs and capacity optimization, while LCA-based studies evaluate environmental performance independently. More recently, integrated frameworks have begun to combine technical and economic dimensions, yet comprehensive assessments that simultaneously capture the causal propagation from capacity expansion to tariff outcomes and environmental burdens remain scarce [25–27]. In particular, the feedback effects of dynamic penetration characteristics: curtailment rates, utilization rates, and extreme event durations on end-user electricity prices and monetized environmental costs have rarely been considered within a unified analytical structure. DPRAF addresses this gap by adopting a structured perspective that explicitly models penetration as

a mediating variable, thereby linking upstream capacity decisions to downstream electricity prices and environmental governance costs within a coherent, full-chain analytical framework.

The main contributions of this paper are as follows:

The original Mixed-Integer Linear Programming (MILP) system capacity planning was optimized by introducing a one-dimensional search to improve it into a two-stage integrated system planning algorithm of capacity Linear Programming (LP) optimization and MILP verification.

A multi-dimensional statistical analysis was conducted on the hourly dynamic changes in penetration rate, revealing the underlying factors, mechanisms, and energy system structure that influence these changes.

This paper develops a parameterized electricity tariff simulation module applicable to rule-based regulated monopolies. The module explicitly embeds multiple institutional mechanisms (e.g., rolling-window Fuel Clause Adjustment, stabilization fund payout, and rebate clauses) and enables explicit attribution of exogenous renewable and levelized cost of hydrogen storage (LCHS) to end-user tariffs. All institutional parameters are adjustable, making the module transferable to other regulated power systems.

By coupling ex ante life cycle analysis (LCA) (with IAM (Integrated Assessment Model)-integrated predictive inventories) with the statistical diagnostics of penetration dynamics (curtailment rate, extreme-event duration), this paper quantifies a non-linear escalation mechanism between renewable capacity expansion and monetized environmental governance costs. This coupling enables a multi-objective trade-off assessment between economic affordability and environmental sustainability in energy transition planning.

Table 1. Relevant literature on the influence of technical factors on penetration rate.

	Energy Storage	Grid Technology & Planning	Control Strategy & Demand Response Plan	Forecasting Technology & Optimization	RE Generation Integration Scale	RE Diversity	Distributed Generation	Artificial Intelligence & Machine Learning	Network & Blockchain
Shahzad et al. [10]	•	•	•	•					
Kaushik et al. [11]	•	•	•		•	•			
Cavus et al. [9]	•	•	•				•	•	
Quizhpe et al. [12]	•							•	•
Kiasari et al. [28]	•	•						•	
Shafiul et al. [15]	•		•	•			•	•	
Liu et al. [13]	•		•	•					
Yu et al. [14]	•	•				•	•	•	•
Sofian et al. [29]	•	•				•		•	
McPherson et al. [18]	•								
Dalala et al. [30]	•			•					
Meltem et al. [8]	•	•	•						
Arabzadeh et al. [31]				•		•			

2. Dynamic Penetration-Rate-Driven Analytic Framework

As shown in Figure 1, this study establishes a four-module, full-chain analysis framework driven by dynamic penetration rates (DPRAF). Within this framework, the hourly dynamic penetration rate serves as an intrinsic real-time feedback mechanism, reflecting the dynamic evolution of energy production and consumption structures. Through this key structural indicator, the impacts of technological factors, specifically grid-connected wind power capacity and hydrogen energy storage deployment, are dynamically transmitted to downstream electricity prices and environmental governance

costs. The operational sequence of these four modules is as follows: (1) optimal capacity configuration based on mixed-integer linear programming (MILP) [32] coupled with one-dimensional search; (2) simulation-based extraction and statistical characterization of the dynamic renewable penetration rate; (3) rule-based modeling of electricity tariff formation under a strongly regulated, regionally monopolistic market; and (4) environmental governance cost assessment using ex ante life cycle assessment (LCA) [33].

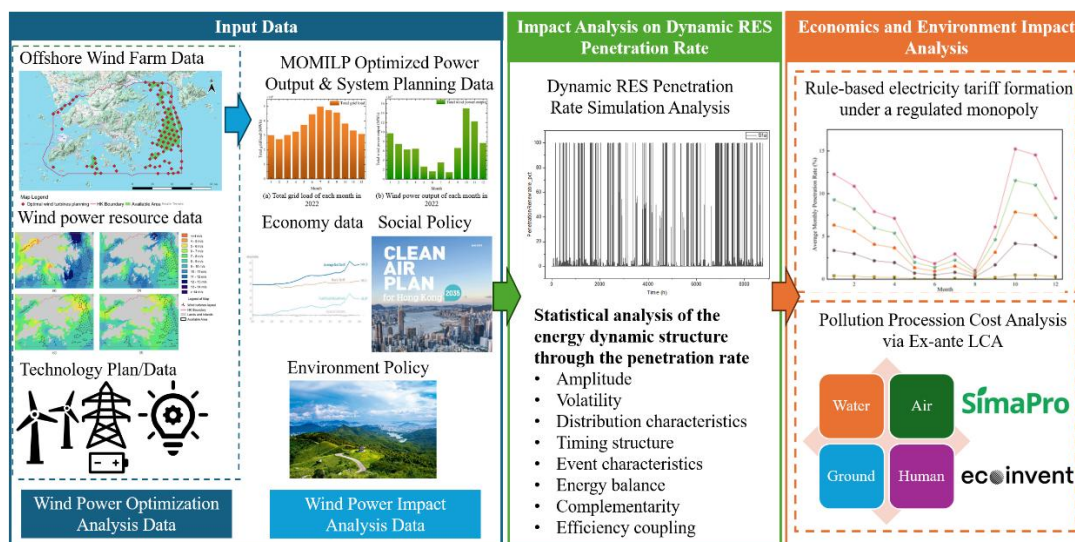


Figure 1. Workflow chart of the dynamic penetration-rate-driven analysis framework (DPRAF).

2.1. MOMILP System Optimization and Simulation

This section introduces methods for system modeling and capacity optimization planning to maximize penetration rates across scenarios with varying grid connection scales and hydrogen-energy storage options. As shown in Figure 2, the offshore wind power-hydrogen energy storage modeling in this paper is based on previous research [34]. Offshore wind power serves as a power source, prioritizing the supply of electricity to meet grid demand. Any surplus is then electrolyzed to produce hydrogen for storage. When wind power is insufficient to meet grid demand, hydrogen is produced to generate electricity for the grid supply. This design aims to leverage hydrogen's high energy density and environmental friendliness to realize the full benefits of renewable energy. Both the electronic cell and fuel cell in the system employ proton exchange membrane technology for rapid response, while pressurization and liquefaction technologies for hydrogen storage are analyzed. The system also has two working modes: (1) full-time work mode, on which the system will send power to the grid all the time and (2) peak-time work mode, on which the system will only supply electricity during the peak-time period (11:00–14:00, 18:00–22:00), to analyze the performance of the system under different task requirements.

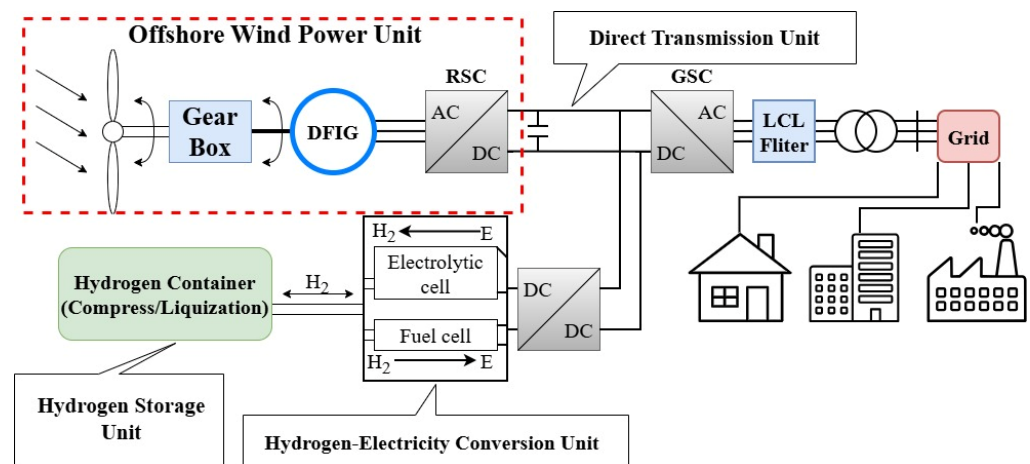


Figure 2. Topography of the offshore wind power-hydrogen energy storage system.

Based on existing research [34], this paper proposes a two-stage system optimization–verification method that combines mixed-integer linear programming and one-dimensional search to improve solution efficiency in the overall model optimization process. As shown in Figure 3, the optimization process is divided into upper-level system capacity planning and lower-level operation planning. The upper-level planning combines linear programming and one-dimensional search and utilizes MATLAB’s built-in golden section and parabolic interpolation algorithms [35] to obtain the optimal power-supply task ratio and system plan under different operating modes, grid connection scales, and energy-storage technology selections. The objective function as shown in Equation (1) below is to maximize the total system output, which consists of direct power supply P_t^{DPO} and hydrogen generated power supply P_t^{FC} :

$$\max \sum_{n=1}^{8760} (P_t^{DPO} + P_t^{FC}) \quad (1 \leq t \leq 8760, t \in \mathbb{Z}^+), \quad (1)$$

The results are input into the next-level operation optimization process and verified using mixed-integer linear programming to confirm whether they meet the physical feasibility requirements of each facility [36,37], such as minimum complexity rate, ramp rate, and start/stop constraints. The object function in this is as Equation (2) shown below, which adds the impact of pre-heating cost:

$$\max [\sum_{n=1}^{8760} (P_t^{DPO} + P_t^{FC}) - \sum_t (P_t^{st.el} + P_t^{st.fc})] \quad (1 \leq t \leq 8760, t \in \mathbb{Z}^+), \quad (2)$$

The modeling details of this part are described in Appendix A.1, Appendix A and the constraints of optimization are listed in Appendix A.2. The optimization results generated hourly time-series data on system power generation and real-time penetration rate for each scenario. These time-series data will serve as input for the statistical analysis in Section 2.2 and subsequent economic and environmental assessments.

The MILP model employs constant efficiency values (60% for electrolyzers and 55% for fuel cells) rather than variable efficiency curves. This simplification is justified because the study focuses on macro-level capacity planning and annual energy balance; furthermore, optimization results indicate that the electrolyzers and fuel cells primarily operate within the 60–80% rated load range, where the efficiency fluctuation for PEM technology is approximately 5–10%. Incorporating non-linear efficiency curves would transform the MILP into a MINLP, significantly increasing computational costs while yielding limited policy-relevant benefits; consequently, dynamic efficiency modeling is reserved for future work.

The one-dimensional search within the high-level planning framework employs the power allocation ratio—representing the split between direct wind power grid integration and the hydrogen production pathway—as the decision variable. For a given wind power capacity and energy storage technology, the system's total output exhibits a unimodal distribution with respect to this ratio, ensuring convergence to a global optimum; the one-dimensional search results presented in followed results align with those of the full-transmission baseline case across all scenarios except SOL, further validating the effectiveness of this simplification.

Key model assumptions—including constant efficiency values, the two operating modes (full-time vs. peak-time), and the scenario definitions (0, 8, 16, 24, 32 GW)—are summarized in Table A1 and discussed in Sections 2.1 and 3.2.

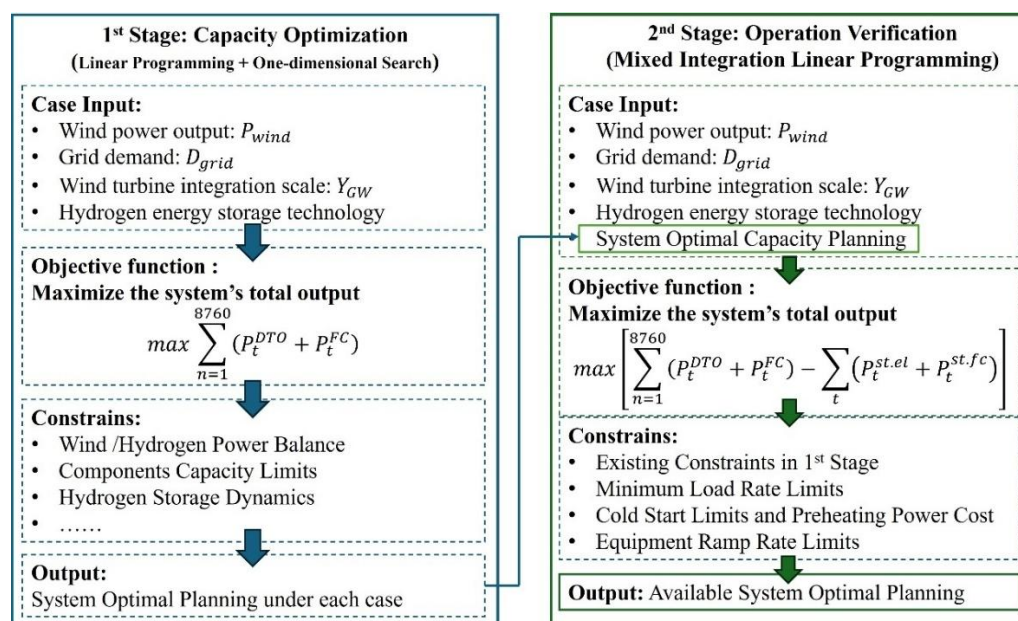


Figure 3. Workflow chart of the bi-level optimization–verification method.

2.2. Statistical Analysis of the Dynamic Renewable Energy Penetration and Energy Structure

This section aims to analyze changes in dynamic penetration rates and other indicators across different scenarios, assess the impact of the scale of grid-connected wind power and the selection of hydrogen storage technology, and examine the dynamic changes in the energy system structure. This section will perform simulation calculations based on the optimal system planning results from the previous stage to generate hourly dynamic renewable energy penetration rate data for each hour throughout the year. The dynamic penetration rate data R_t^{RE} at time point t was calculated as Equation (3) follows:

$$R_t^{RE} = \frac{[P_t^{DTO} + P_t^{FC}]}{D_{grid}(t)} \quad (1 \leq t \leq 8760, t \in \mathbb{Z}^+), \quad (3)$$

The obtained dynamic RE penetration rate will be statistically analyzed to interpret the real-time changes in the energy structure. This part will analyze four aspects: (1) penetration rate level and distribution characteristics, (2) volatility and time dynamics, (3) extreme events and system balance, and (4) source complementarity and efficiency coupling, to obtain comprehensive analysis results. The statistical results for each aspect are presented in Section 3.3, providing the diagnostic context for the economic and environmental analyses that follow.

2.3. Electricity Tariff Analysis Under Regulated Monopoly

This section aims to analyze how dynamic changes in RE penetration rate, driven by the scale of grid-connected wind power and the choice of hydrogen energy storage technology, affect electricity prices in a market environment characterized by strong regulation and regional monopolies. So, the market mechanism references Stackelberg's "leader-follower" structure [38], where government regulatory agencies, as leaders, pre-set price rules and regulatory agreements, while power companies, as followers, formulate strategies based on these rules to optimize their own operations. However, this type of market is not suitable for the traditional Stackelberg–Cournot model because it lacks the price-game equilibrium mechanism and instead relies on rules to allocate operating costs [39,40].

Therefore, as shown in Figure 4, this paper constructs a three-layer transmission model to reflect the impact of renewable energy penetration in the market. The first layer is to calculate the conventional generation requirement P_t^{ff} at time point t as Equation (4) shown:

$$P_t^{ff} = D_{grid} - (P_t^{DTO} + P_t^{FC}) + (P_t^{st,el} + P_t^{st,fc}) \quad (1 \leq t \leq 8760, t \in \mathbb{Z}^+), \quad (4)$$

Here, D_{grid} represents grid demand, P_t^{DTO} is directly transmitted power at t hour, P_t^{FC} is power generated from hydrogen, and $P_t^{st,el}$ and $P_t^{st,fc}$ are the power consumed by the operation of the electrolyzer and fuel cell, respectively.

Then the second layer will carry out the fossil fuel cost C^{ff} of the specific month m as Equation (5) shown:

$$C^{ff} = \sum_t (C_{kWh}^{fuel} \times \phi^f \times P_t^{ff}) \quad (1 \leq t \leq m, t \in \mathbb{Z}^+), \quad (5)$$

Here, C_{kWh}^{fuel} is the price of fossil fuel per unit, and ϕ^f is a fuel price multiplier that reflects market fluctuations.

The pricing mechanism investigated in this paper employs a rolling-window approach to determine the fuel clause adjustment (FCA); specifically, the adjustment charge for month m depends on the average fuel cost calculated over a window comprising the preceding N months. Based on this, the FCA for month m is calculated as shown in Equation (6):

$$FCA_m = \begin{cases} FCA^{base}(m \leq N) \\ FCA^{base} + \left(\frac{\sum_{i=m-N}^{m-1} C_i^{ff}}{\sum_{i=m-N}^{m-1} D_i} - C^{ff,pr} \right) (m > N) \end{cases} \quad (6)$$

Based on the result above, the third layer will determine the power price/tariff P_t with Equation (7) as follows:

$$P_t = P_t^{base} + FCA_m + C^{wind} \times \frac{R_m}{D_m} + c^{H2} \times \frac{R_m}{D_m} - F_m^{pay} - R^{reb}, \quad (7)$$

$$F_m^{pay} = \max(0, FCA_m - FCA^{base}) \times \gamma \quad (\gamma \in [0,1]), \quad (8)$$

Here, P_t^{base} is the stipulated benchmark electricity price, C^{wind} is the exogenous levelized cost of wind power, c^{H2} is the exogenous levelized cost of hydrogen energy storage, R_m is the renewable energy demand for the month, D_m is the total grid demand for the month, F_m^{pay} is the disbursement from the electricity price stabilization fund, and R^{reb} is the discount. γ is the payout ratio that absorbs a fraction of the FCA increase beyond the baseline.

Therefore, we can use the three-layer model described above to analyze the mechanism of energy price changes under rate-of-return regulatory framework.

Layer 1: Conventional Generation Requirement

$$P_t^{ff} = D_{grid} - (P_t^{DTO} + P_t^{FC}) + (P_t^{st,el} + P_t^{st,fc}) \quad (t \in \mathbb{Z}^+)$$

**Layer 2: Fossil fuel Cost of special month**

$$C^{ff} = \sum_t (C_{kWh}^{fuel} * \phi^f * P_t^{ff}) \quad (1 \leq t \leq m, t \in \mathbb{Z}^+)$$

$$FCA_m = \begin{cases} FCA^{base} & (m \leq N) \\ FCA^{base} + \left(\frac{\sum_{i=m-N}^{m-1} C_i^{ff}}{\sum_{i=m-N}^{m-1} D_i} - C^{ff,pr} \right) & (m > N) \end{cases}$$

**Layer 3: Regulatory cost-pass-through**

$$P_t = P_t^{base} + FCA_m + C^{wind} * \frac{R_m}{D_m} + c^{H2} * \frac{R_m}{D_m} - F_m^{pay} - R^{reb}$$

Figure 4. The workflow chart of the three layers of the electricity tariff determination.

2.4. Environmental Governance Cost Analysis Based on Ex Ante LCA

This section will analyze the environmental impact and its impact on environmental governance costs based on the previously obtained system configuration scheme and penetration rate results, using the ex ante LCA method [33]. The workflow of ex ante LCA is like that of the conventional LCA method, including (1) goal and scope definition, (2) life cycle inventory analysis (LCI), (3) life cycle impact assessment (LCIA), and (4) interpretation. However, the main difference between ex ante LCA and LCA is that ex ante LCA uses predictive data from experiments and theories to estimate impact factors, whereas LCA summarizes past statistics. Therefore, ex ante LCA is more suitable than LCA for analyzing the relevant effects under long-term scenarios, and is also more applicable to the study in this paper [41].

This paper will use the professional LCA software SimaPro (10.1 version) in conjunction with the Ecovient database (3.10 version) for analysis, and manually configured the 2035 background electricity mix based on Hong Kong's 2035 Future Energy Plan to enable scenario-specific ex ante LCA.

The specific ex ante LCA settings are as follows. The system boundary is cradle-to-gate, covering raw material extraction, manufacturing, transport, and installation of offshore wind turbines and hydrogen storage infrastructure, excluding grid connection, transmission losses, and end-of-life decommissioning. The functional unit is 1 MWh of electricity delivered to the grid. The impact categories comprise eight ReCiPe 2016 Mid-point (H) indicators: global warming, fine particulate matter formation, marine eutrophication, marine ecotoxicity, terrestrial acidification, terrestrial ecotoxicity, human carcinogenic toxicity, and human non-carcinogenic toxicity. The scenario setting for the

2035 background electricity mix is manually constructed based on Hong Kong's 2035 Future Energy Plan, without relying on Integrated Assessment Model (IAM) projections. Monetization is performed using the Environmental Prices (2019) EU27 central method, which applies shadow prices to convert characterized results into USD. The data sources include the Ecoinvent v3.10 database for background processes, with the offshore wind process represented by 'electricity production, wind, 1–3 MW turbine, offshore, CN-GD' and the baseline grid represented by 'electricity production, high voltage, HK', reflecting Guangdong's offshore wind resources and Hong Kong's existing electricity structure.

3. Discussion of Results

3.1. Case Study: Hong Kong

This paper studies a comprehensive scenario set in Hong Kong, China. Located on the southern edge of the East Asian continent, adjacent to Guangdong Province and facing the South China Sea, Hong Kong possesses natural advantages for developing and leveraging offshore wind energy resources. Simultaneously, Hong Kong has a dense population, developed industries, high energy consumption, and a high dependence on external fossil fuels. The development of renewable energy is crucial for Hong Kong's energy stability and security, as well as environmental protection [42]. These factors constitute the prerequisites for Hong Kong to independently develop or collaborate on the offshore wind energy industry with Guangdong Province [43].

In previous work, the authors conducted a planning analysis of the available offshore wind power development areas in Hong Kong, derived the optimal wind farm scheme (Figure 5), and simulated the wind power output and grid demand by hour with the Markov method [34]. The prediction data of typical day with weak wind power output or abundant output are shown in Figure 6. The research described in this paper will be further developed based on the work mentioned above.

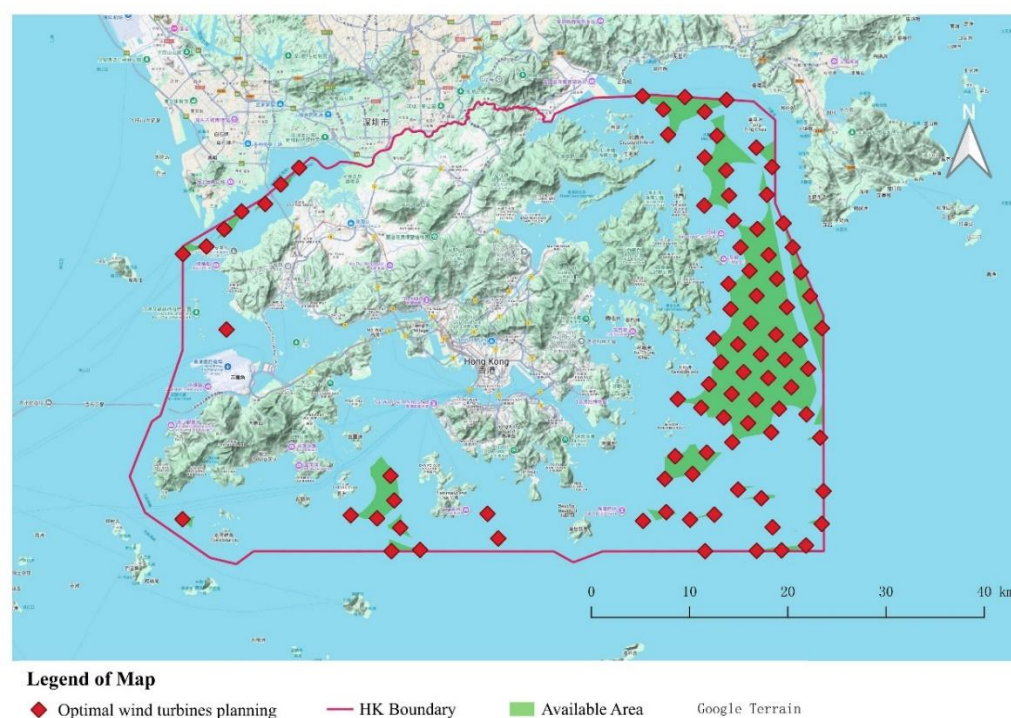


Figure 5. The optimal planning of the offshore wind farm in Hong Kong [44]. (Place names in the image are labeled in both Chinese and English).

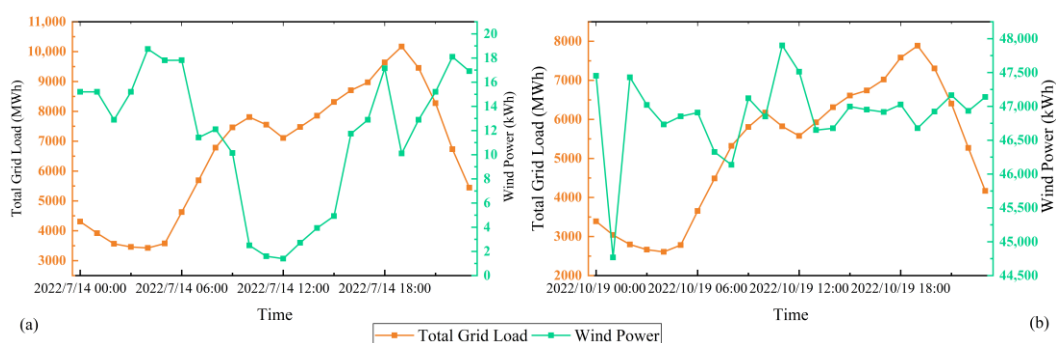


Figure 6. The prediction of the wind power and grid demand in Hong Kong on the typical day with weak wind power (a) and abundant wind power (b) in 2022.

Considering the gap in scale between wind power output and grid demand in previous work, this study will consider incorporating a portion of the wind power capacity in the Guangdong coastal area into the Hong Kong power grid to analyze the combined impact of expanding grid-connected wind turbine capacity and the corresponding application of hydrogen energy storage technology on the penetration of renewable energy. This article will set up five scenarios to simulate the results of the gradual expansion of grid-connected capacity in the future (up to 2035), including only Hong Kong wind power (1.056 GW), and, on this basis, adding 8 Giga Watt (GW), 16 GW, 24 GW, and 32 GW of offshore wind power capacity in Guangdong.

The output of these wind power projects ultimately depends on Hong Kong's energy system mechanisms to have any impact. The Hong Kong government has established a pricing mechanism with two local regional monopoly power companies through the Scheme of Control Agreement (SoC). This framework follows a rate-of-return (ROR) regulatory model, in which the utility's allowed revenue is determined by its prudently incurred costs plus a regulated return on its asset base. This mechanism makes the electricity price consist of four parts: (1) a basic tariff negotiated every five years, (2) a fuel charge calculated from the energy costs of the previous two months and the estimated energy costs, (3) a surcharge generated from the acquisition of output from private renewable energy systems, and (4) special rebates. This rate-of-return-based structure and pricing mechanism, which is not based on market equilibrium but on specific rules under strong regulation, is the most concrete case studied in this article. The study will refer to the agreement between the Hong Kong Special Administrative Region government and the China Light and Power (CLP) Group, which the basis tariff is 0.937 Hong Kong Dollar (HKD)/kWh and special rebate is 0.034 HKD/kWh [45]. The relevant economic and policy parameters are shown in Table 2 below:

Table 2. Relevant economic and policy parameters.

Parameter Symbol	Parameter Meaning	Value	Unit	Source/Explanation
p_t^{base}	Basic tariff	0.937	HKD/kWh	[45]
FCA^{base}	Basic FCA	0.386	HKD/kWh	[46]
$C^{ff.pr}$	Predicted fuel cost per unit	0.281	HKD/kWh	No open data, apply basic FCA in 2021, [47]
ϕ^{nor}	Fuel price coefficient (normal situation)	1.0		
ϕ^{cri}	Fuel price coefficient (crisis situation)	2.8		Estimate based on the FCA increase in 2022, [48]
γ	Fund allocation ratio	0.73		[45]

R^{reb}	Special rebate	0.034	HKD/kWh	[45]
N	FCA rolling window length	3		[45]
C^{wind}	Levelized cost of offshore wind power	0.63	HKD/kWh	[44]
$C^{H2,com}$	Levelized cost of compressed hydrogen storage	0.077	HKD/kWh	[49]
$C^{H2,liq}$	Levelized cost of liquefied hydrogen storage	0.22	HKD/kWh	[49]

3.2. Wind–Hydrogen System Optimal Capacity Planning Results

As shown in Table 3, based on the algorithm in Section 2.1, this study obtained optimized system configurations for various scenarios.

Table 3. Optimal capacity planning results.

Cases	Wind Power Capacity (GW)	Hydrogen Storage Mode	System Work Mode	Optimal Peak-Shaving Ratio (%)	System Energy Efficiency (%)	Electronic Cell Capacity (MW)	Fuel Cell Capacity (MW)	Hydrogen Container Capacity (kg)	System Total Power Output (MWh)	Total Hydrogen Production (kg)
S0L	1.056	Liquification	Full-time Peak-time	61.85 99.99	88.36 41.53	0.025 38.463	0.43 369.6	11.111 29,545.735	80,962 24,753	0 745,858.05
S8P	9.056	Compression	Full-time Peak-time	38.28 61.85	88.36 44.83	0.001 374.314	0.084 1764.393	11.111 119,744.749	694,486 236,618	0 6,878,564.33
S8L			Full-time Peak-time	20.74 71.6	88.36 41.53	0.011 329.847	0.441 3169.6	11.111 253,377.062	694,475 212,283	0 6,396,297.85
S16P	17.056	Compression	Full-time Peak-time	94.43 94.36	88.36 44.83	0.001 704.98	0.084 3323.045	11.111 225,526.33	1,307,991 445,645	0 12,955,034.59
S16L			Full-time Peak-time	62.9 99.99	88.36 41.53	0.006 621.231	0.429 5969.6	11.111 477,208.39	1,307,985 399,812	0 12,046,737.6
S24P	25.056	Compression	Full-time Peak-time	67.79 99.99	88.36 44.83	0.001 1035.646	0.084 4862.357	11.111 331,307.91	1,921,495 661,400	0 19,030,764.1
S24L			Full-time Peak-time	61.57 99.99	88.36 41.53	0.006 912.615	0.429 6570.709	11.111 701,039.717	1,921,488 576,627	0 17,867,929.66
S32P	33.056	Compression	Full-time Peak-time	74.21 99.99	88.36 44.83	0.003 1366.311	0.084 5504.875	11.111 437,089.491	2,534,997 903,623	0 25,072,142.4
S32L			Full-time Peak-time	75.35 99.99	88.36 41.47	0.009 1203.999	0.427 6220.083	11.111 924,871.044	2,534,990 835,569	0 23,572,888.05

The current optimization results combine two modes: a one-dimensional search to find the optimal peak-shaving transmission task ratio and a pre-set unlimited transmission mode, such as a task ratio of 100%, with the grid fully open to renewable energy. The aim is to compare the similarities and differences between the two schemes. However, in terms of results, aside from the absence of effective results when grid-connected wind power capacity is zero, and pressurized hydrogen storage is used, the results of the two optimization modes are identical in all other scenarios. This verifies that the power-supply capacity of the wind–hydrogen system must be subject to a physical system limit. Beyond this limit, changes in the task ratio will not affect the optimal system capacity scheme and performance.

Based on the characteristics of the data, these optimization results can be divided into three categories by grid-connected wind power scale. For a 0 GW integrated wind power capacity, only the liquefied hydrogen storage solution is feasible. This is due to the low wind power capacity and output level. The grid has sufficient capacity to accommodate the wind power in most cases, so there is no need for hydrogen production (such as in pressurized hydrogen storage scenarios), or the demand for hydrogen production is very small. That is, the optimal system capacity tends to be 0. The second scenario, as seen with S8L and S8P,

involves a conflict between the increased system output level and the grid's capacity to absorb power, forcing optimization to weigh the two. Consequently, cases S8L and S8P exhibit relatively low optimal peak-shaving task ratios across all optimization schemes in both scenarios. The third scenario is when the scale of grid-connected wind power expands to a certain level, such as S16 and S32. The significant increase in wind power output makes the benefits of this expansion clearly outweigh the penalties associated with the increased scale; thus, the corresponding optimal peak-shaving task ratio also increases, approaching 1. These three scenarios constitute the three main states under which existing power grids should cope with the energy acceptance of newly integrated renewable energy sources.

3.3. Statistical Analysis of Dynamic RE Penetration Rate and Energy System Structure

Following the four-dimensional framework defined in Section 2.2, the statistical results are presented below. Based on the optimization results described above, this study conducted modeling and simulation in MATLAB R2026a to calculate real-time permeability changes. The comparison results include cases without hydrogen energy storage (cases with the “N” sign, such as S0N). The results are shown in Figure 7.

The simulation results, showing the hourly variation in penetration rate, indicate that the main factor influencing the level of renewable energy penetration remains the grid-connected renewable energy installed capacity, with a positive correlation between the two. The impact of energy storage technology selection is relatively weak, as this portion of energy consumption (such as operating and pre-heating energy consumption) accounts for a relatively small share overall and becomes increasingly insignificant as grid-connected capacity increases. This difference in penetration rate or output loss caused by technology selection and application is spread over the entire year, so in terms of image presentation, the curves of schemes with the same RE integration scale almost completely overlap. This characteristic was also clearly demonstrated in subsequent statistical analyses.

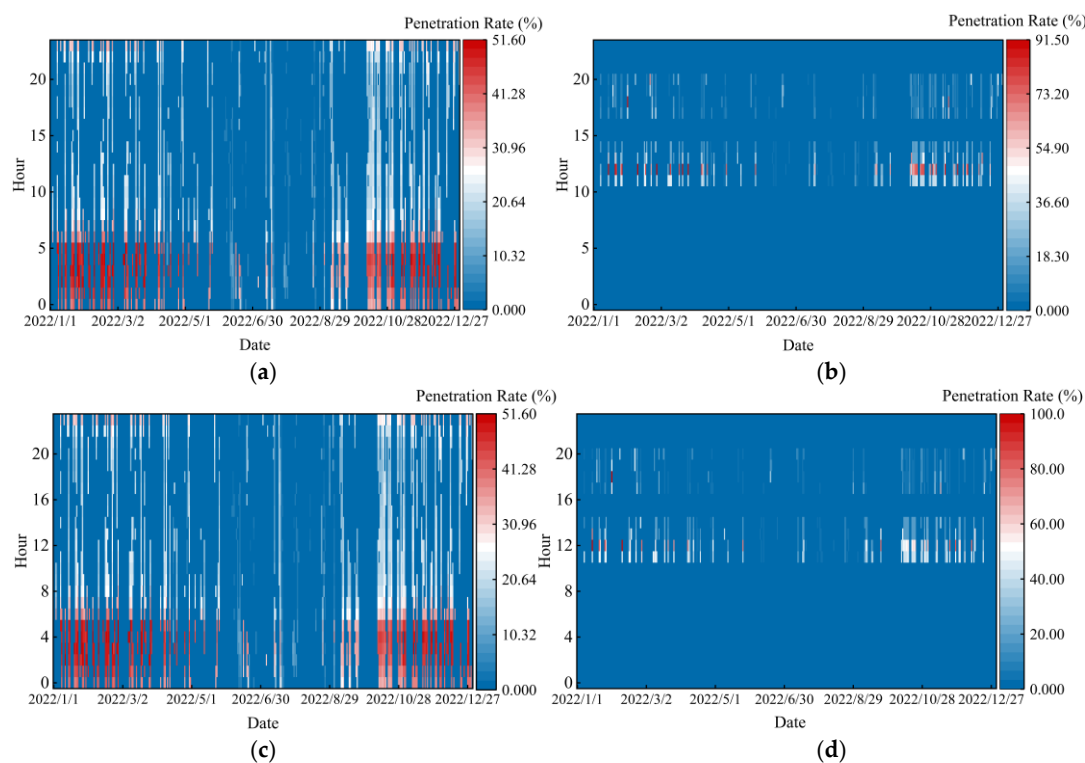


Figure 7. Heatmap of hourly penetration rate changes in full-time work mode (a,c) and peak-time work mode (b,d) scenarios of cases S24P (a,b) and S24L (c,d) in 2022.

As shown in Figure 7, the results show a very clear seasonal correlation and a positive correlation between penetration rate changes and grid-connected wind power capacity. The trough for offshore wind power production in Hong Kong occurs in summer, hence the lower real-time penetration rate during summer, while higher penetration rates are observed in autumn and winter when wind resources are more abundant. At the same time, the larger installed capacity of wind power also brings higher raw power input, thereby increasing the overall penetration rate. The impact of adopting and selecting hydrogen energy storage technology is not significant on the evolution of the hourly penetration rate.

The monthly penetration rate results shown in Figure 8 are like those in Figure 7. Differences in wind power output and overall installed capacity across different months create a stratified pattern in the monthly variation curves. However, another noteworthy feature is that the impact of differences in the application and selection of hydrogen energy storage technology is particularly evident in the monthly average data, especially under peak-hour regulation operating modes. Moreover, as installed capacity increases, the effectiveness of the hydrogen energy storage system improves, amplifying the originally insignificant efficiency differences. Therefore, we can see the differentiation of the monthly average curves under a large installed capacity. The difference between these two charts also reveals that the impact of hydrogen energy storage systems on dynamic penetration rates is cumulative. It has a slight impact on the real-time renewable energy production and sales structure but has an objective effect on increasing the penetration rate over a long-term scale.

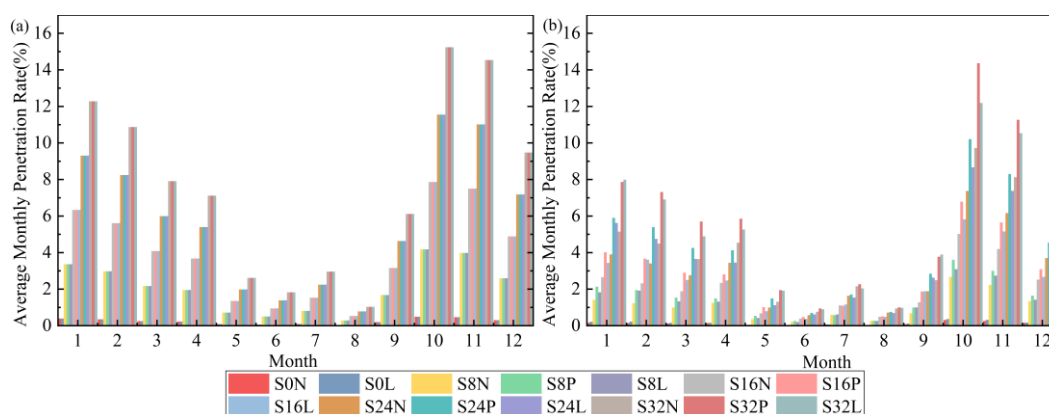


Figure 8. Changes in average monthly penetration rate in full-time work mode (a) and peak-time work mode (b) scenarios in 2022.

To address extreme situations during operation, this paper, based on IEA standards, defines events with penetration rates below 20% as low-penetration events and those above 80% as high-penetration events [50]. As shown in Figure 9, the extreme-event data indicate that, under full-time peak-shaving mode, the effect of hydrogen energy storage technology on improving overall penetration in small-scale wind power grid-connected scenarios remains limited. However, in peak-hour operating mode, as the scale of grid-connected capacity and hydrogen energy storage increases, system flexibility improves, and the duration of low penetration is significantly reduced. Based on the results of the scale variation in system power shortages, this paper also found similar characteristics in hydrogen energy storage systems. Among them, the overall efficiency of pressurized hydrogen storage is higher than that of liquefied hydrogen storage. Therefore, pressurized hydrogen storage schemes operating under the same mode and with the same grid-connected wind power capacity often have shorter durations of low-power events and a smaller scale of system power shortages than liquefied hydrogen storage.

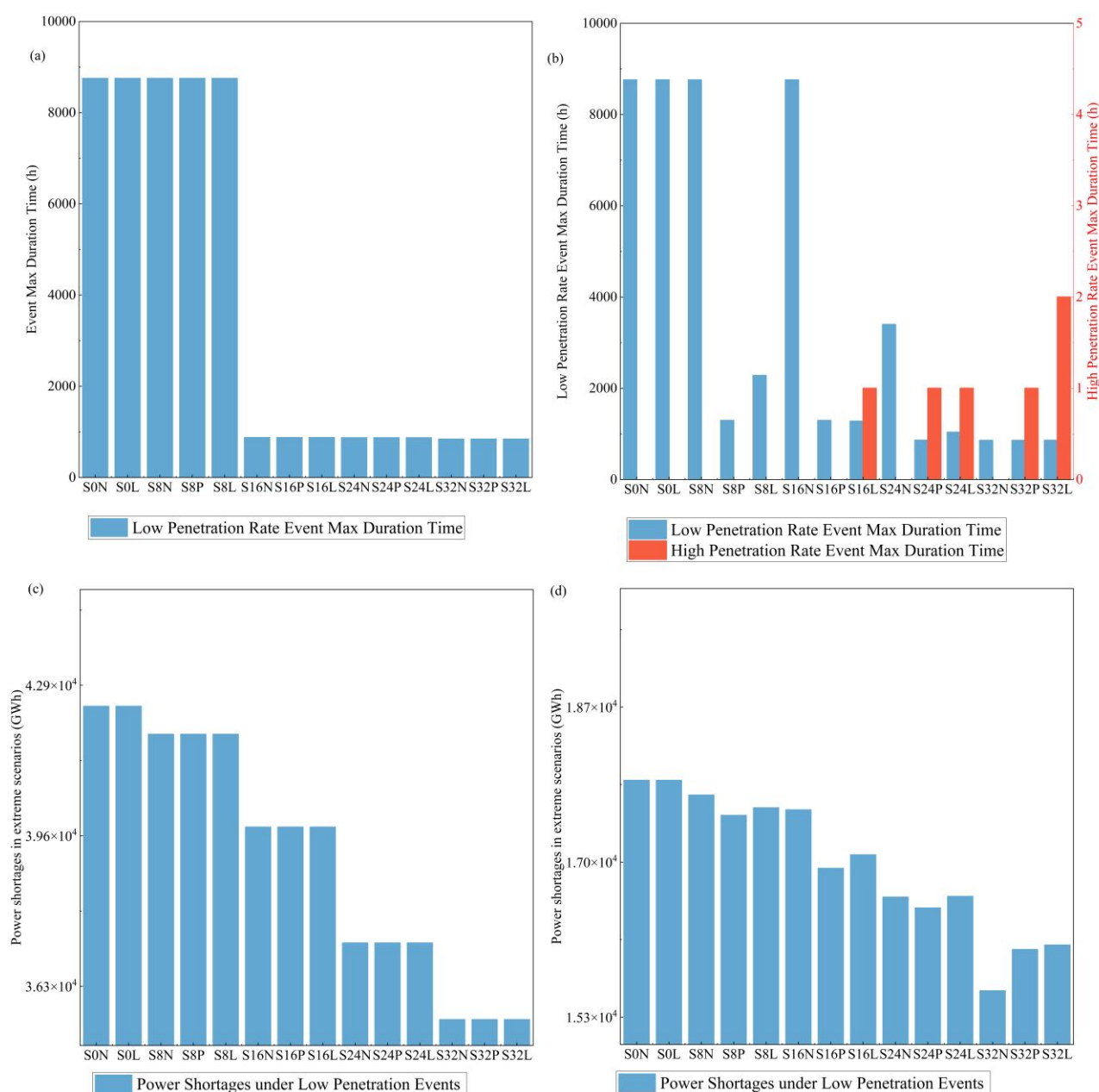


Figure 9. Duration of extreme penetration rates and power shortages in full-time work mode (a,c) and peak-work mode (b,d) scenarios.

Figure 10 illustrates three coupling indicators for the peak-period operation scenario. First, the reduction in the power deficit increases linearly with the installed wind power capacity. Second, under the peak-period operating mode utilizing hydrogen energy storage, the correlation between wind power and hydrogen energy varies by storage technology: compressed storage maintains a moderate positive correlation (0.554–0.614) that gradually strengthens as capacity increases, whereas liquefied storage starts with a lower correlation (0.229) but catches up to 0.542 at 32 GW, exhibiting a steeper growth trend. This indicates that both technologies can achieve comparable levels of wind–hydrogen coupling at scale, albeit through different pathways: compressed storage relies on higher round-trip efficiency, while liquefied storage relies on greater absorption capacity. Third, the correlation between curtailed wind energy and electrolyzer input power remains high across all peak-period scenarios, with liquefied storage (0.928–0.933)

performing slightly better than compressed storage (0.903–0.904); this demonstrates that both technologies effectively utilize curtailed wind energy, with liquefied storage holding a slight advantage in terms of absorption capacity.

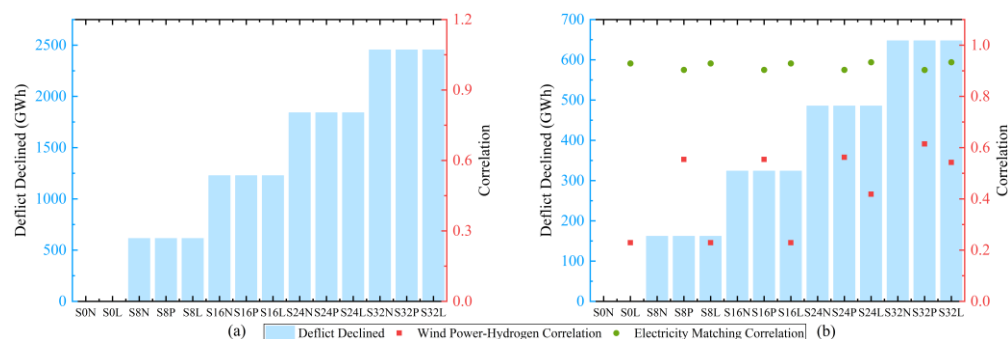


Figure 10. Wind–hydrogen energy coupling in full-time work mode (a) and peak-time work mode (b) scenarios.

3.4. Price-Determining Mechanism Analysis and Electricity Tariff Result

Based on the aforementioned research, we analyzed electricity price fluctuations following the grid integration of renewable energy. As fuel adjustment charges remained relatively stable with minimal variation during January and February, this study focuses on price changes from March onwards. Figure 11 illustrates that monthly electricity price fluctuations are significantly influenced by variations in wind conditions and installed wind farm capacity. Under peak-period operating modes—which incorporate hydrogen production and energy storage during off-peak hours—the application and technical configuration of energy storage systems exert a more pronounced impact on electricity prices compared to continuous operation scenarios; however, the accumulation of associated costs drives prices up, resulting in a rate approximately 0.1 HKD higher than the standard level.

Due to the implementation of an eight-month electricity price freeze and rebate measures in Hong Kong in 2022, the actual electricity prices (i.e., prices net of rebates) from March to August were lower than the price levels simulated in this study for a scenario incorporating renewable energy. However, driven by global energy market volatility in 2022 and the resumption of the price adjustment mechanism in September of that year, the electricity price under the renewable energy scenario did not fall below the actual price until November—even during the autumn and winter months when wind resources are abundant. This result directly demonstrates that expanding the grid integration of renewable energy (specifically offshore wind power) does not have a positive effect on lowering electricity prices.

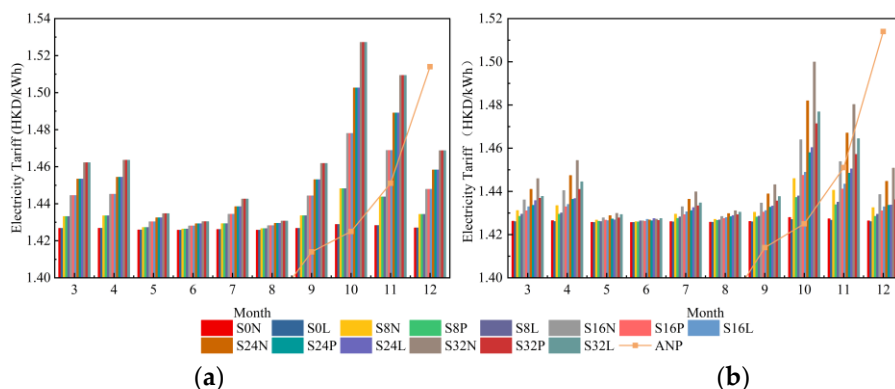


Figure 11. Comparison of average monthly electricity price changes (Mar–Dec) and actual net electricity prices (ANP) under full-time work mode (a) and peak-time work mode (b) scenarios.

The average annual electricity price exhibits a similar trend. As shown in Figure 12, the expansion of grid-connected wind power capacity is the primary factor driving down electricity prices, whereas the application of energy storage technologies may actually lead to price increases. Specifically, under both operating modes, every 8 GW increase in grid-connected offshore wind capacity results in a rise of approximately HKD 0.004 per kWh in the electricity price. The impact of hydrogen storage technology is more pronounced under the peak-period operating mode. Notably, the price increase associated with liquid hydrogen storage is lower than that of high-pressure hydrogen storage, and this disparity becomes increasingly evident as the scale of grid-connected wind power expands. Despite the overall downward trend in electricity prices, the price gap per kWh between these two hydrogen storage solutions will widen from approximately HKD 0.0005 to HKD 0.0007.

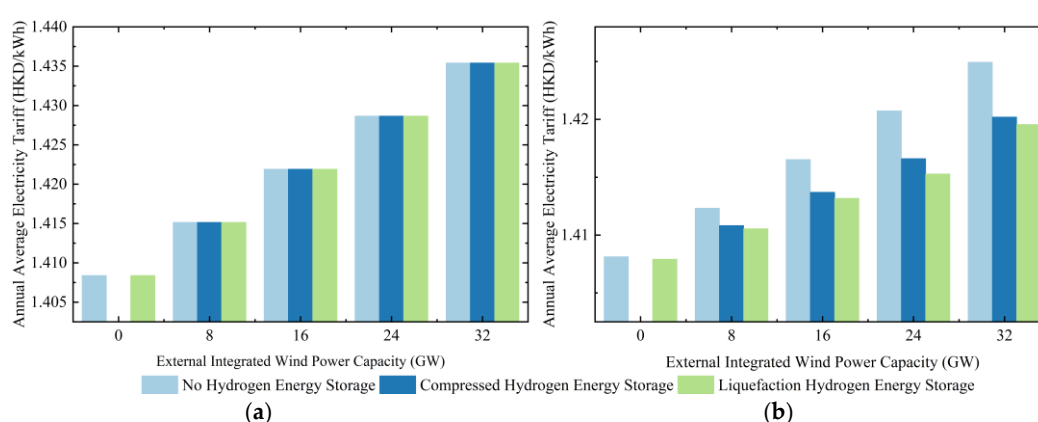


Figure 12. Annual average electricity price under full-time work mode (a) and peak-time work mode (b) scenarios.

The core reason for this situation lies in the composition of electricity tariffs in Hong Kong. As shown in Figure 13, the basic tariff and the Fuel Clause Adjustment (FCA) account for a significant portion of the electricity price; these components experienced the most pronounced volatility and increases in 2022 and are difficult to mitigate through limited wind and hydrogen power integration. Furthermore, as illustrated in Figure 14, while the expansion of grid-connected wind farm capacity has led to a reduction in the FCA, the rate of reduction in fund allocations has slowed, and the allocated costs associated with wind energy and hydrogen storage have risen. Consequently, despite the adoption of wind power and hydrogen storage, electricity prices remain higher than usual given the limited penetration levels. At the same time, because the wind power penetration rate for the liquid hydrogen energy storage scheme is lower than that of the schemes without hydrogen storage or with pressurized hydrogen storage, the renewable energy-related costs passed on to electricity prices are lower; consequently, the liquid hydrogen storage scheme—despite being more energy-intensive—actually results in lower electricity prices.

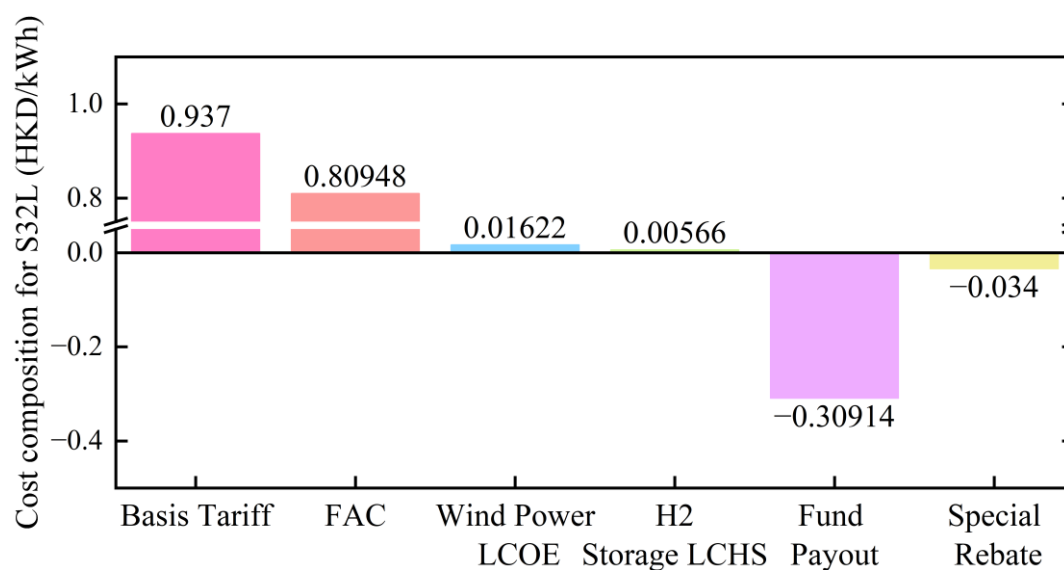


Figure 13. Annual average electricity tariff composition under scenario S32L with peak-time work mode.

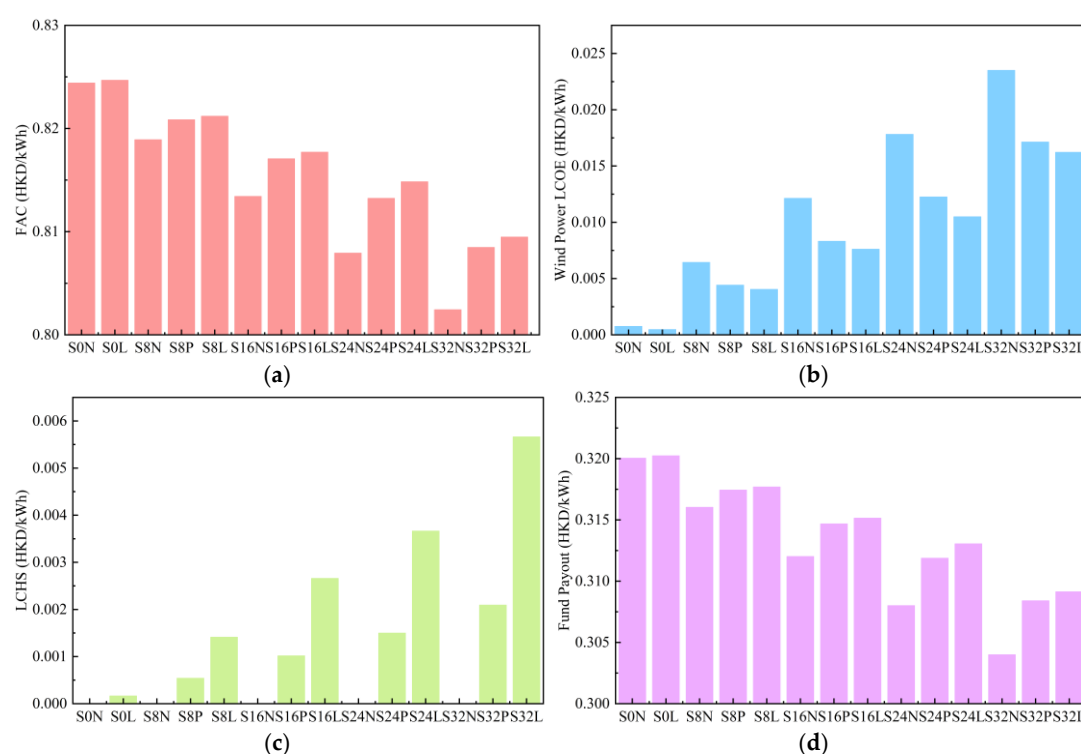


Figure 14. Changes in the cost composition of electricity prices under different scenarios: (a) FCA, (b) wind power LCOE, (c) hydrogen energy storage LCHS and (d) fund payout.

Regarding the comparison between monthly price changes and fuel cost adjustment fee changes, based on the results in Figures 11 and 15, this paper discovers a mechanism for electricity price capping caused by the upper limit of the fuel cost adjustment fee. This “flat-top” upper-limit mechanism is due to insufficient wind power output during specific periods, causing electricity and fuel cost adjustment fees to gradually converge and even overlap at the same level across different scenarios. As wind power output increases and fuel costs are reduced at different levels, the curve shape will change from flat-top to

arched, as shown by the difference between the grid-integrated wind power capacities of 0 GW and 32 GW.

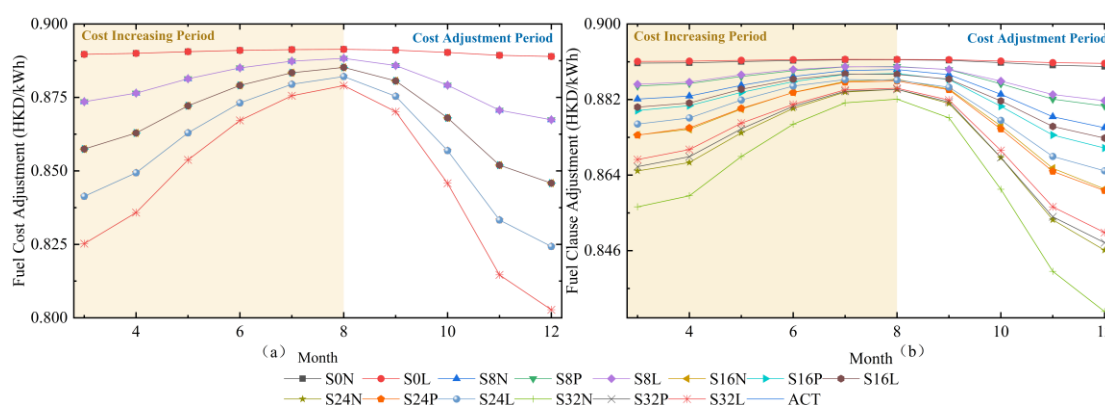


Figure 15. Monthly fuel cost adjustment fee changes (Mar–Dec) in full-time work mode (a) and peak-time work mode (b) scenarios and the real fuel cost adjustment fee (ACT).

The monotonic tariff increase observed here contrasts with findings from competitive wholesale markets in the work of Cacciarelli et al., where wind power has been shown to exhibit a U-shaped price effect—reducing prices at low penetration but converging to zero at moderate levels [51]. This divergence reflects the fundamental difference in price formation: competitive markets operate through supply-demand equilibrium, whereas regulated monopoly tariffs are governed by institutional cost-pass-through mechanisms (Equations (6)–(8)), where infrastructure costs are directly allocated to end-users. The common expectation that ‘renewables lower electricity prices’, valid in wholesale markets, thus does not automatically translate to regulated settings.

The tariff module developed in this study is calibrated for Hong Kong’s rate-of-return regulatory framework, where all prudently incurred costs are pass-through items ultimately recovered from end-users. This pass-through logic explains why renewable capacity expansion translates directly into tariff increases rather than triggering competitive price responses. For deregulated competitive markets, the tariff module would require replacing the cost-pass-through logic with a market-clearing equilibrium mechanism, like Stackelberg–Cournot or Nash-type models, as the current Stackelberg-inspired ‘leader-follower’ structure is contingent upon the presence of a regulatory authority. This adaptation is identified as a future research direction rather than a capability of the current formulation.

The distinction between these two market types delineates the module’s boundary. By contrast, for regulated jurisdictions that share the same cost-recovery logic, the module is directly transferable with parameter recalibration. This near-linear relationship is a direct consequence of the rate-of-return regulatory framework. Renewable investments thus translate predictably into tariff increases, making tariffs a function of cost structure rather than market dynamics. This pattern is consistent with international experience: Hong Kong’s Scheme of Control belongs to a broader family of cost-recovery-based frameworks [52], found in the U.S. (cost-of-service regulation) [53], Canada (ROR coexisting with price-cap alternatives) [54], and Europe [55] (WACC-based allowed-return rules). Even jurisdictions that have adopted price-cap or performance-based reforms have built upon, rather than abandoned, this cost-based tradition. Hong Kong is therefore not an isolated case, but a clear example of a regulatory class that shares common trade-offs among efficiency, investment, and consumer protection—enhancing the framework’s transferability provided local parameters are recalibrated.

3.5. Environmental Governance Cost and Regulatory Implications

Based on the work, this paper is able to fully estimate the marginal environmental impact of the system's power generation in 2035 using the ex ante LCA method. This paper references Hong Kong's 2035 Future Energy Plan and pioneers a simple model of the anticipated energy structure, thereby enabling a comparative and quantitative analysis of the environmental impact of wind power-hydrogen power. The methodological settings, including system boundary, functional unit, impact categories, and monetization framework, are detailed in Section 2.4.

In the characterization stage, this study used the ReCiPe mid-point (2016) method for life cycle impact assessment, and the results are shown in Table 4. This study found that among the eight indicators selected based on four dimensions—atmosphere, ocean, land, and human habitation—marine environmental toxicity, soil environmental toxicity, and human carcinogenicity were the indicators that actually increased after renewable energy systems replaced the original share of electricity generation. Conversely, emissions of greenhouse gases and inhalable particulate matter, ocean eutrophication, and soil acidification, as well as non-carcinogenic toxicity to humans, have decreased. This part of the environmental impact mainly stems from pollution generated during the manufacturing and installation of offshore wind power and hydrogen power systems. This type of pollution is absent in Hong Kong's energy system, which is dominated by thermal power generation. Furthermore, the replacement of traditional thermal power by renewable energy has reduced the impact of traditional thermal power on key areas, particularly greenhouse gas emissions, inhalable particulate matter, and soil acidification.

This study also conducted a monetization study on related energy governance costs. Using the Environment Price mid-point (2019) method, this quantitative analysis revealed, as shown in Figure 16, that the expansion of grid-connected renewable energy capacity leads to a significant increase in overall environmental governance costs. For every additional 8 GW of grid-connected wind power capacity, the final annual overall environmental governance cost will increase by approximately 21 million USD. Furthermore, under peak-hour operating conditions, pressurized hydrogen storage technology incurs higher environmental governance costs than liquefied hydrogen storage technology. This difference widens with the expansion of grid-connected capacity; for example, 8 GW would increase environmental governance costs by 0.8 million USD annually, but in a 32 GW scenario, this difference would expand to an additional 2 million USD annually. When further disaggregating this trend by scenario, a critical distinction emerges: without hydrogen storage, both the electricity tariff and environmental cost rise near-linearly (approximately increasing by 0.0042 HKD/kWh and 5.54 million USD per 8 GW, respectively). With hydrogen storage, however, the environmental cost increment accelerates from approximately 7.15 million USD (8 to 16 GW) to 8.29 million USD (24 to 32 GW) for pressurized storage, and from 6.42 million to 8.86 million USD for liquefied storage over the same intervals. This divergence indicates that the environmental burden of hydrogen-equipped systems does not scale proportionally with capacity, with the 16–24 GW interval marking the onset of accelerated growth and the 24–32 GW range exhibiting the most pronounced divergence.

Regarding the monetization approach, the aggregation of eight impact categories into a single governance cost inevitably embeds value judgments, as it applies EU27-centered shadow prices to local contexts. This choice follows the standard practice of the Environmental Prices (2019) method and is intended to provide a consolidated metric for policy comparison. To test the robustness of the results, a sensitivity analysis was conducted using ReCiPe 2016 Endpoint (H) with the World (2010) H/A weighting set,

which produces weighted scores in Pt rather than USD. Under this alternative framework, the 16 GW scenario consistently outperforms the 32 GW scenario, confirming that the identification of the 16–24 GW corridor as the preferred trade-off range is robust to the choice of monetization methodology. Nevertheless, the absolute values and the direction of individual impact categories vary across methods, underscoring the importance of focusing on relative scenario comparisons rather than absolute monetary values. Previous LCA studies on offshore wind–hydrogen systems, whether focused on supply chain comparisons [56] or on integrated system assessments [57], have reported similar patterns, including the lower efficiency of liquefied hydrogen and the significance of marine toxicity as a key impact category. However, these studies report static per-unit impacts without linking them to penetration-driven utilization factors. Our analysis extends beyond these works by revealing that monetized environmental costs escalate non-linearly when capacity expansion outpaces grid absorption capacity—a mechanism that emerges only when infrastructure burdens are amortized over declining effective generation output.

Therefore, based on current research findings, this paper argues that future policies for the grid connection, development, and utilization of renewable energy systems should fully consider the increased costs of residential electricity and environmental governance. Within the 16–24 GW range, the carbon-reduction benefits remain roughly commensurate with the incremental governance costs, making this a pragmatic reference corridor under Hong Kong’s current regulatory framework. Beyond the 24 GW threshold, the non-linear escalation of both tariffs and environmental costs suggests that regulators should exercise caution in approving further large-scale grid connections without complementary mitigation measures. It should be acknowledged, however, that the present LCA quantifies only the direct environmental burdens of manufacturing and installation; it does not incorporate the mitigating effects of life-cycle interventions such as component recycling, material substitution, or green manufacturing processes. These measures, which could substantially reduce the elevated marine and soil toxicity identified in the results, are recommended as a priority for future research.

Table 4. Comparison of life cycle impact characterization results between Hong Kong grid baseline and offshore wind power (per MWh delivered to grid).

Impact Category	Unit	Grid Baseline (per MWh)	Wind Power (per MWh)	Difference (Wind – Grid)
Global warming	kg CO ₂ eq	374	17.2	−356.8
Fine particulate matter formation	kg PM _{2.5} eq	0.0471	0.0352	−0.0119
Marine eutrophication	kg N eq	0.00171	0.00127	−0.00044
Marine ecotoxicity	kg 1,4-DCB	5.28	7.9	+2.62
Terrestrial acidification	kg SO ₂ eq	0.00232	0.0704	+0.06808
Terrestrial ecotoxicity	kg 1,4-DCB	1.16E3	1.38E3	+220
Human carcinogenic toxicity	kg 1,4-DCB	22.1	43.5	+21.4
Human non-carcinogenic toxicity	kg 1,4-DCB	102	49.3	−52.7

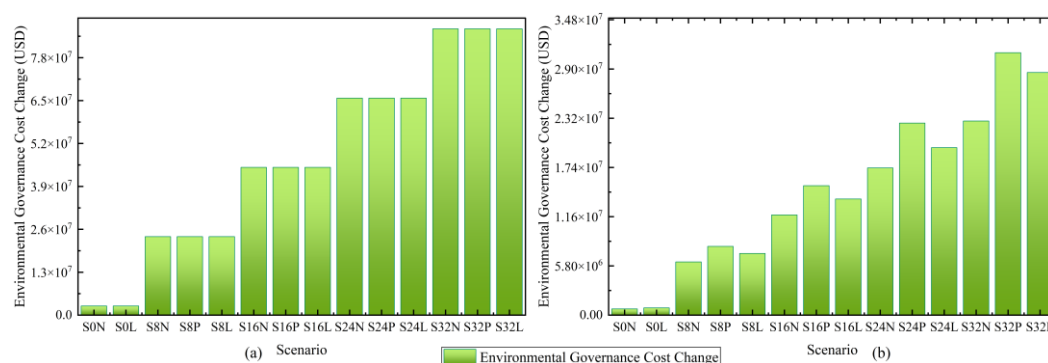


Figure 16. Increase in environmental governance monetization costs in full-time (a) and peak-time (b) scenarios.

4. Conclusions and Policy Suggestions

This paper develops a comprehensive dynamic penetration-rate-driven analytical framework (DPRAF) to examine how offshore wind power grid connection scale and hydrogen energy storage technology selection influence renewable energy penetration rate and dynamic energy structure, as well as electricity prices and environmental governance costs.

Key contributions of the work include:

(1) A two-stage optimization–verification framework is proposed, combining mixed-integer linear programming (MILP) with a one-dimensional search. This design overcomes the computational intensity of conventional MILP formulations and improves the efficiency of capacity planning and operational analysis.

(2) A multi-dimensional statistical diagnostic framework is established to characterize the hourly penetration dynamics from four complementary angles: level and distribution, volatility and temporal patterns, extreme events, and source–load coupling. These diagnostics serve as the interpretive basis for the subsequent economic and environmental assessments.

(3) A parametric tariff pass-through module is developed for rate-of-return regulatory framework markets. The module embeds institutional mechanisms—including a rolling-window Fuel Clause Adjustment (FCA), a stabilization fund payout, and exogenous LCOE stacking for wind and hydrogen storage—with all institutional parameters tunable for transferability to other regulated systems. Simulation results show that a larger wind grid connection scale raises the absolute tariff to 0.004 HKD per 8 GW under peak-time mode, with hydrogen storage further increasing the tariff; the magnitude of the increase is moderated by the fund payout mechanism.

(4) Using ex ante LCA (with IAM-integrated predictive inventories), this study quantifies eight environmental impact indicators across four dimensions and monetizes the resulting governance costs. The results reveal a non-linear escalation of monetized environmental costs with wind capacity expansion, driven by rising curtailment rates and declining utilization efficiency, which together amplify the per-unit environmental burden of the deployed infrastructure.

Based on current research findings, this paper argues that future renewable energy policies should fully consider the increased costs of residential electricity and environmental governance. The 16–24 GW grid-connected wind capacity range is identified as a pragmatic reference corridor under Hong Kong's current regulatory framework. While this framework shares the pass-through logic common to many major economies, the specific numerical threshold is contingent on local cost structures and institutional

parameters. In alternative regulatory regimes, such as price-cap or performance-based models, the tariff response to renewable expansion would follow different dynamics, suggesting that the framework's transferability lies in its parametric structure rather than in the numerical values themselves. Beyond the 24 GW threshold, the non-linear escalation of both tariffs and environmental costs suggests that regulators should exercise caution without complementary mitigation measures. Future work should also explore life-cycle intervention strategies—such as recycling of turbine and electrolyzer components and low-impact material selection—to mitigate the increased marine and soil toxicity associated with renewable infrastructure deployment. For regions with limited space, pressurized hydrogen storage is preferable due to its higher round-trip efficiency; for ecologically sensitive areas, liquefied storage may be favored given its lower monetized environmental governance costs. This site-specific trade-off highlights the need for multi-criteria assessments that incorporate local spatial and environmental constraints into the planning framework.

It should be acknowledged that the 16–24 GW corridor is conditional on the current cost and regulatory parameters (e.g., fossil fuel prices, FCA mechanism, and no explicit carbon pricing). Future carbon taxes or sustained fossil fuel price volatility could shift this equilibrium—higher carbon prices would increase the economic advantage of renewable generation, potentially expanding the optimal capacity range. While such dynamic economic feedbacks are not modeled in the current framework, they represent a critical direction for future work to enhance the policy relevance of the analytical framework.

Author Contributions: Conceptualization, L.Y. and L.L.; Methodology, L.Y.; Formal analysis, L.Y.; Investigation, L.Y.; Resources, L.Y.; Writing—Original draft, L.Y.; Writing—Review & Editing, L.Y. and L.L.; Visualization, L.Y.; Funding acquisition, L.L.; Supervision, L.L.; Project administration, L.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by Hong Kong RGC General Research Fund (GRF), PI, Development of a Novel Solar PV/T Structure with Built-in Non-Uniform EPCCM Heat Storage Units for Smart Cooling of Solar PV Modules, HK\$1,066,054.00, Project No.15219323.

Institutional Review Board Statement: Not available.

Informed Consent Statement: Not available.

Data Availability Statement: The data referenced and analyzed in this paper originate from an earlier, unpublished study that utilized meteorological observation data from the Hong Kong Observatory and statistics from the Census and Statistics Department of the Hong Kong Special Administrative Region. While the meteorological observation data are not publicly available, the data from the Census and Statistics Department are publicly accessible for independent consultation.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Abbreviations

The following abbreviations are used in this manuscript:

DPRAF	Dynamic penetration-rate-driven analytical framework
FCA	Fuel Clause Adjustment
HKD	Hong Kong Dollar
LCA	Life cycle analysis
LCI	Life cycle inventory analysis
LCIA	Life cycle impact assessment

LCOE	Levelized cost of energy
LCHS	Levelized cost of hydrogen storage
MILP	Mixed integer linear programming
RE	Renewable energy

Appendix A

Appendix A.1. The Modeling of the System

Appendix A.1.1. Wind Power System

Offshore wind turbines are the only energy source for this system, and their power output is mainly determined by the rated power of the turbine itself and the ambient wind speed [58]. At the same time, the output of the wind farm is also subject to the layout of each unit in the wind farm, so the overall output at hour t is as shown in Equations (A1) and (A2) [59]:

$$P_{Wind}(t) = \sum_{i=1}^n P_{WT,i}(t) \quad (1 \leq t \leq T, t \in \mathbb{N}), \quad (A1)$$

$$P_{WT,i}(t) = \begin{cases} 0 & V(t) < V_{in} \text{ or } V(t) \geq V_{out} \\ P_{TS} \times \frac{V(t) - V_{in}}{V_{TS} - V_{in}} & V_{in} \leq V(t) < V_{TS} \\ P_{TS} & V_{TS} \leq V(t) < V_{out} \end{cases} \quad (1 \leq t \leq T, t \in \mathbb{N}) \quad (A2)$$

For this, $V(t)$ is the wind speed of the unit per hour, V_{in} is the inflow wind speed, V_{TS} is the rated wind speed corresponding to the rated power P_{TS} , and V_{out} is the cut-out wind speed. The wind power output $P_{WT,i}(t)$ of a single wind turbine at t hour is obtained, and the hourly output $P_{Wind}(t)$ of the wind farm is the sum of the outputs of all units.

Appendix A.1.2. Direct Transmission System

Wind power output is divided into two paths: directly transmitted to the urban power grid via high-voltage direct current or injected into the electrolytic cell to produce hydrogen for energy storage, then fed into the urban power grid through fuel cells for power generation when needed. This part of the power output to the grid can be calculated as Equations (A3) and (A4):

$$P_{in,t}(t) = P_{in,d}(t) \times (1 - \eta_{rec,d}) \quad (1 \leq t \leq T, t \in \mathbb{N}), \quad (A3)$$

$$P_{DTo}(t) = P_{in,t}(t) \times (1 - \eta_{inv,d}) \quad (1 \leq t \leq T, t \in \mathbb{N}) \quad (A4)$$

$P_{in,d}(t)$ is the part of wind power at t hour output that is directly injected into the grid via high-voltage direct current transmission. The power under high-voltage direct current transmission is $P_{in,t}(t)$, which has been processed by the rectifier. The actual power $P_{DTo}(t)$ injected into the grid needs to take into account the loss caused by the secondary conversion required for AC-DC-AC transmission [60]. The system efficiency loss of the rectifier and inverter are $\eta_{rec,d}$ and $\eta_{inv,d}$.

Appendix A.1.3. Electricity-to-Hydrogen Conversion Model

As a part of the hydrogen-electricity conversion path, the electricity-to-hydrogen conversion device includes electrolytic cells and rectifiers, which are also the core part of this capacity optimisation study.

The electrolysis device consists of multiple electrolytic cells of uniform specifications connected in parallel to obtain a higher total working current and reaction rate. The

energy conversion and output of the electrolysis part are calculated as Equations (A5) and (A6) below:

$$P_{EL}(t) = P_{IE}(t) \times \eta_{EL} \quad (1 \leq t \leq T, t \in \mathbb{N}), \quad (\text{A5})$$

$$P_{IE}(t) = P_{in.e}(t) \times (1 - \eta_{rec.e}) \quad (1 \leq t \leq T, t \in \mathbb{N}) \quad (\text{A6})$$

where $P_{EL}(t)$ is the working power of the electrolytic cell at t hour and fuel cell. $P_{IE}(t)$ is the input power from wind power at t hour. η_{EL} is the average power efficiency of the electrolytic cell, which is calculated with the reversible voltage, voltage loss of polarization, and Faraday efficiency [61]. Therefore, the electrolysis output $P_{HO}(t)$ of the electrolysis unit at t hour can be simply calculated with low-heat value (LHV) of hydrogen as Equation (A7) follows:

$$P_{HO}(t) = \frac{P_{EL}(t)}{LHV(H_2)} \quad (1 \leq t \leq T, t \in \mathbb{N}, LHV(H_2) \approx 33.3), \quad (\text{A7})$$

Appendix A.1.4. Hydrogen Storage Model

The hydrogen in this system does not consider the loss during storage and transmission, so it is directly measured by electricity with theoretical energy equivalent. The storage of hydrogen $P_{SH}(t)$ at t hour can be calculated as Equation (A8):

$$\begin{aligned} P_{SH}(t) &= P_{SH}(t-1) + P_{HO}(t) - P_{FO}(t) \\ (0 \leq P_{SH}(t) \leq S_{tank}, 0 \leq P_{SH}(t-1) \leq S_{tank}, \\ 1 \leq t \leq T, t \in \mathbb{N}) \end{aligned} \quad (\text{A8})$$

where $P_{SH}(t-1)$ is the stored hydrogen at the last hour and $P_{HO}(t)$ is the produced hydrogen at the t hour and $P_{FO}(t)$ is the consumed. Both $P_{SH}(t-1)$ and $P_{SH}(t)$ cannot exceed the maximum capacity S_{tank} of the hydrogen container.

Appendix A.1.5. Hydrogen-to-Electricity Conversion Model

Hydrogen-to-electricity conversion system is another core part of the hydrogen-electricity conversion path. The calculation for this part is as shown in Equations (A9) and (A10) [62]:

$$\begin{aligned} P_{FC}(t) &= P_{IF}(t) \times LHV(H_2) \times \eta_{EL} \times \delta_t(t) \\ (0 \leq P_{IF}(t) \leq P_{SH}(t), 1 \leq t \leq T, t \in \mathbb{N}, \delta_t(t) = \{0,1\}) \end{aligned} \quad (\text{A9})$$

$$P_{FO}(t) = P_{FC}(t) \times (1 - \eta_{inv.f}) \quad (1 \leq t \leq T, t \in \mathbb{N}) \quad (\text{A10})$$

This part of the output control is based on the peak load demand of the power grid and the hydrogen inventory at that time. Among them, $P_{FO}(t)$ is the actual output of the hydrogen power system to the power grid, that is, the result of the fuel cell output $P_{FC}(t)$ being produced by the inverter. $\eta_{inv.f}$ is the system efficiency loss of the inverter. δ_t is the working status index of the fuel cell, which equals 0 or 1.

Appendix A.1.6. The Relevant Technical Parameters

The parameters in the optimization task are shown in the following table:

Table A1. The technical parameters.

Symbol	Meaning	Values and Unit
T	Total time	Hour
η_{inv}	The system efficiency loss rate of the inverter	2%

η_{rec}	The system efficiency loss rate of the rectifier	2%
$LHV(H_2)$	The low-heat value of hydrogen	About 33.3 kWh/kg [63]
η_{EL}	The system efficiency of the electrolytic cell	About 60% [64]
η_{FC}	The system efficiency of the fuel cell	About 55% [65]
C_{max}^{wind}	The maximum output capacity of the wind farm	1,056,000 kW
r	The share rate of the peak shaving task period to the total grid load	0~100%

Appendix A.2. System Constraints and Boundary Conditions

This study constructs a constraint system for optimization work based on three dimensions, as follows:

Appendix A.2.1. Constrains1: Wind Power Balance

Since the power generated by the wind farm is the only energy source in this system, the sum of the power allocated to the two paths in the system should equal the total power output of the wind farm, as in Equation (A11) below:

$$P_{wind}(t) = P_{in.d}(t) + P_{in.e}(t) \quad (1 \leq t \leq T, t \in \mathbb{N}), \quad (A11)$$

Appendix A.2.2. Constrains2: Facilities' Power and Capacity

The system load factor of the electrolytic cell and fuel cell is an important variable for system capacity optimization and is calculated as Equation (A12) shown:

$$\begin{cases} R_{EL} = P_{EL}(t)/S_{elec} \\ R_{FC} = P_{FC}(t)/S_{fc} \end{cases} \quad (1 \leq t \leq T, t \in \mathbb{N}), \quad (A12)$$

During the optimization process, the solver will select the optimal component capacity based on real-time working power changes and the reference theoretical optimal load rate. Due to the polarization effect, the optimal load ratio for the efficiency of the electrolytic cell and fuel cell is roughly in the range of 60–80% [66].

At the same time, as a device for the flow of current into and out of the system, the power of the converter also constitutes a limitation to the power, as shown in Equation (A13):

$$\begin{cases} P_{in.d}(t) \leq S_{rect.d} \\ P_{in.t}(t) \leq S_{inv.d} \\ P_{in.e}(t) \leq S_{rect.e} \\ P_{FC}(t) \leq S_{inv.f} \end{cases} \quad (1 \leq t \leq T, t \in \mathbb{N}), \quad (A13)$$

Similarly, the operating power of the electrolytic cell and fuel cell is also limited by the total rated power of the overall capacity, as shown in Equation (A14):

$$\begin{cases} P_{IE}(t) \leq S_{elec} \\ P_{IF}(t) \times LHV(H_2) \leq S_{fc} \end{cases} \quad (1 \leq t \leq T, t \in \mathbb{N}), \quad (A14)$$

Considering the security, the hydrogen storage tank will have a 10% security margin, as shown in Equation (A15):

$$0 \leq P_{SH}(t) \leq 0.9 \times S_{tank}, \quad (A15)$$

Appendix A.2.3. Constrains3: System Capacity

In this study, the equivalent storage power of the system's hydrogen storage tank capacity should not be less than half of the sum of the total power of the electrolytic cell and the fuel cell. Therefore, its total output power is subject to the following constraints, as shown in Formula (A16):

$$S_{tank} \geq 0.5 \times (S_{elec} + S_{fc}), \quad (A16)$$

The total power capacity of the electrolytic cell and fuel cell should not be greater than the total power output of the wind farm, as shown in Equation (A17):

$$\begin{cases} S_{elec} \leq C_{max}^{wind} \\ S_{fc} \leq C_{max}^{wind} \end{cases}, \quad (A17)$$

To prevent the hydrogen storage tank from expanding indiscriminately during the optimization calculation, its upper limit is limited to 30×24 times the maximum hourly hydrogen production to cope with specific high wind power output months, as shown in Equation (A18):

$$S_{tank} \leq 30 \times 24 \times P_{HO}(t) \quad (1 \leq t \leq T, t \in \mathbb{N}) \quad , \quad (A18)$$

References

1. Ríos-Ocampo, J.P.; Arango-Aramburo, S.; Larsen, E.R. Renewable energy penetration and energy security in electricity markets. *Int. J. Energy Res.* **2021**, *45*, 17767–17783. <https://doi.org/10.1002/er.6897>.
2. Xu, T.; Gao, W.; Qian, F.; Li, Y. The implementation limitation of variable renewable energies and its impacts on the public power grid. *Energy* **2022**, *239*, 121992. <https://doi.org/10.1016/j.energy.2021.121992>.
3. Mladenov, V.; Chobanov, V.; Georgiev, A. Impact of Renewable Energy Sources on Power System Flexibility Requirements. *Energies* **2021**, *14*, 2813. <https://doi.org/10.3390/en14102813>.
4. Liu, G.; Dou, D.; Wang, Y.; Li, X.; Gao, Z.; Lv, H. Multi-scenario flexibility requirement analysis of high proportion of new energy access to power system. *Clean Energy* **2024**, *8*, 187–204. <https://doi.org/10.1093/ce/zkae090>.
5. Al kez, D.; Foley, A.M.; McIlwaine, N.; Morrow, D.J.; Hayes, B.P.; Zehir, M.A.; Mehigan, L.; Papari, B.; Edrington, C.S.; Baran, M. A critical evaluation of grid stability and codes, energy storage and smart loads in power systems with wind generation. *Energy* **2020**, *205*, 117671. <https://doi.org/10.1016/j.energy.2020.117671>.
6. Pavlík, M.; Kurimský, F.; Ševc, K. Renewable Energy and Price Stability: An Analysis of Volatility and Market Shifts in the European Electricity Sector (2015–2025). *Appl. Sci.* **2025**, *15*, 6397. <https://doi.org/10.3390/app15126397>.
7. Li, G.; Yang, J.; Wu, F.; Zhu, X.; Ke, S.; Li, Y. A Market Framework for a 100% Renewable Energy Penetration Spot Market. *IEEE Trans. Sustain. Energy* **2023**, *14*, 1569–1584. <https://doi.org/10.1109/tste.2023.3239415>.
8. Peker, M.; Kocaman, A.S.; Kara, B.Y. Benefits of transmission switching and energy storage in power systems with high renewable energy penetration. *Appl. Energy* **2018**, *228*, 1182–1197. <https://doi.org/10.1016/j.apenergy.2018.07.008>.
9. Cavus, M. Advancing Power Systems with Renewable Energy and Intelligent Technologies: A Comprehensive Review on Grid Transformation and Integration. *Electronics* **2025**, *14*, 1159. <https://doi.org/10.3390/electronics14061159>.
10. Shahzad, S.; Jasińska, E. Renewable Revolution: A Review of Strategic Flexibility in Future Power Systems. *Sustainability* **2024**, *16*, 5454. <https://doi.org/10.3390/su16135454>.
11. Kaushik, E.; Prakash, V.; Mahela, O.P.; Khan, B.; El-Shahat, A.; Abdelaziz, A.Y. Comprehensive Overview of Power System Flexibility during the Scenario of High Penetration of Renewable Energy in Utility Grid. *Energies* **2022**, *15*, 516. <https://doi.org/10.3390/en15020516>.
12. Quizhpe, K.; Arévalo, P.; Ochoa-Correa, D.; Villa-Ávila, E. Optimizing Microgrid Planning for Renewable Integration in Power Systems: A Comprehensive Review. *Electronics* **2024**, *13*, 3620. <https://doi.org/10.3390/electronics13183620>.
13. Liu, S.; Yan, J.; Yan, Y.; Zhang, H.; Zhang, J.; Liu, Y.; Han, S. Joint operation of mobile battery, power system, and transportation system for improving the renewable energy penetration rate. *Appl. Energy* **2024**, *357*, 122455. <https://doi.org/10.1016/j.apenergy.2023.122455>.
14. Yu, Q.; Jiang, Z.; Liu, Y.; Zhang, Y.; Li, L.; Han, X.; Shi, S.; Bai, X. Research of renewable energy penetration rate in integrated energy stations. *Energy Rep.* **2021**, *7*, 33–37. <https://doi.org/10.1016/j.egyr.2021.08.158>.
15. Alam, M.S.; Al-Ismael, F.S.; Salem, A.; Abido, M.A. High-Level Penetration of Renewable Energy Sources Into Grid Utility: Challenges and Solutions. *IEEE Access* **2020**, *8*, 190277–190299. <https://doi.org/10.1109/access.2020.3031481>.
16. Soto, G.H.; Martinez-Cobas, X. Does outward foreign direct investment and the green transition affect renewable energy penetration among European Union countries? *Renew. Energy* **2025**, *241*, 122306. <https://doi.org/10.1016/j.renene.2024.122306>.

17. Yu, B.; Fang, D.; Yu, H.; Zhao, C. Temporal-spatial determinants of renewable energy penetration in electricity production: Evidence from EU countries. *Renew. Energy* **2021**, *180*, 438–451. <https://doi.org/10.1016/j.renene.2021.08.079>.
18. McPherson, M.; Tahseen, S. Deploying storage assets to facilitate variable renewable energy integration: The impacts of grid flexibility, renewable penetration, and market structure. *Energy* **2018**, *145*, 856–870. <https://doi.org/10.1016/j.energy.2018.01.002>.
19. Ahmad, E.; Khan, D.; Anser, M.K.; Nassani, A.A.; Hassan, S.A.; Zaman, K. The influence of grid connectivity, electricity pricing, policy-driven power incentives, and carbon emissions on renewable energy adoption: Exploring key factors. *Renew. Energy* **2024**, *232*, 121108. <https://doi.org/10.1016/j.renene.2024.121108>.
20. Brown, T.; Reichenberg, L. Decreasing market value of variable renewables can be avoided by policy action. *Energy Econ.* **2021**, *100*, 105354. <https://doi.org/10.1016/j.eneco.2021.105354>.
21. Radpour, S.; Gemechu, E.; Ahiduzzaman, M.; Kumar, A. Developing a framework to assess the long-term adoption of renewable energy technologies in the electric power sector: The effects of carbon price and economic incentives. *Renew. Sustain. Energy Rev.* **2021**, *152*, 111663. <https://doi.org/10.1016/j.rser.2021.111663>.
22. Cadoret, I.; Padovano, F. The political drivers of renewable energies policies. *Energy Econ.* **2016**, *56*, 261–269. <https://doi.org/10.1016/j.eneco.2016.03.003>.
23. Chu, L.K.; Ghosh, S.; Doğan, B.; Nguyen, N.H.; Shahbaz, M. Energy security as new determinant of renewable energy: The role of economic complexity in top energy users. *Energy* **2023**, *263*, 125799. <https://doi.org/10.1016/j.energy.2022.125799>.
24. Zhindon-Almeida, R.G.; Ruiz-Carrillo, J.A. Factors Influencing the Adoption of Renewable Energies in Developing Countries. *Sustain. Dev.* **2025**, *33*, 7222–7244. <https://doi.org/10.1002/sd.3490>.
25. Islam, M.T.; Abdul Qadir, S.; Ali, A.; Khan, M.W. Economic and environmental impact assessment of renewable energy integration: A review and future research directions. *Clean. Energy Syst.* **2024**, *9*, 100162. <https://doi.org/10.1016/j.cles.2024.100162>.
26. Amponsah, J.; Ansah, K.K.; Asare, D.B.; Siameh, F.O. Integrated assessment of energy systems: Opportunities and barriers for digital twin and artificial intelligence adoption. *Renew. Sustain. Energy Rev.* **2026**, *236*, 116962. <https://doi.org/10.1016/j.rser.2026.116962>.
27. Park, H. A multi-dimensional framework for comparing zero-carbon energy sources in the energy transition. *Energy Res. Soc. Sci.* **2026**, *136*, 104721. <https://doi.org/10.1016/j.erss.2026.104721>.
28. Kiasari, M.; Ghaffari, M.; Aly, H. A Comprehensive Review of the Current Status of Smart Grid Technologies for Renewable Energies Integration and Future Trends: The Role of Machine Learning and Energy Storage Systems. *Energies* **2024**, *17*, 4128. <https://doi.org/10.3390/en17164128>.
29. Bin Abu Sofian, A.D.A.; Lim, H.R.; Siti Halimatul Munawaroh, H.; Ma, Z.; Chew, K.W.; Show, P.L. Machine learning and the renewable energy revolution: Exploring solar and wind energy solutions for a sustainable future including innovations in energy storage. *Sustain. Dev.* **2024**, *32*, 3953–3978. <https://doi.org/10.1002/sd.2885>.
30. Dalala, Z.; Al-Omari, M.; Al-Addous, M.; Bdour, M.; Al-Khasawneh, Y.; Alkasrawi, M. Increased renewable energy penetration in national electrical grids constraints and solutions. *Energy* **2022**, *246*, 123361. <https://doi.org/10.1016/j.energy.2022.123361>.
31. Arabzadeh, V.; Frank, R. Creating a renewable energy-powered energy system: Extreme scenarios and novel solutions for large-scale renewable power integration. *Appl. Energy* **2024**, *374*, 124088. <https://doi.org/10.1016/j.apenergy.2024.124088>.
32. Mohammed, A.; Ghaithan, A.M.; Al-Hanbali, A.; Attia, A.M. A multi-objective optimization model based on mixed integer linear programming for sizing a hybrid PV-hydrogen storage system. *Int. J. Hydrog. Energy* **2023**, *48*, 9748–9761. <https://doi.org/10.1016/j.ijhydene.2022.12.060>.
33. Buyle, M.; Audenaert, A.; Billen, P.; Boonen, K.; Van Passel, S. The Future of Ex-Ante LCA? Lessons Learned and Practical Recommendations. *Sustainability* **2019**, *11*, 5456. <https://doi.org/10.3390/su11195456>.
34. Ye, L.; Lu, L. Development of a System-Efficiency-Oriented Offshore Wind-Hydrogen Regulation Framework for Urban Grid Reliability. *Renew. Energy* **2026**, *submitted*.
35. Mathwork. fminbnd. Solve Single-Variable Local Minimization Problem on a Fixed Interval. Available online: <https://www.mathworks.cn/help/matlab/ref/fminbnd.html?lang=en#References> (accessed on 5 May 2026).
36. Lin, L.; Li, X.; Ou, K.; Xing, J.; Wang, Y.-X. Mixed integer linear programming-based optimal capacity configuration of ALK/PEM mixed water electrolysis system. *Energy* **2025**, *333*, 137419. <https://doi.org/10.1016/j.energy.2025.137419>.
37. Lamedica, R.; Santini, E.; Ruvio, A.; Palagi, L.; Rossetta, I. A MILP methodology to optimize sizing of PV–Wind renewable energy systems. *Energy* **2018**, *165*, 385–398. <https://doi.org/10.1016/j.energy.2018.09.087>.

38. Sheha, M.; Mohammadi, K.; Powell, K. Techno-economic analysis of the impact of dynamic electricity prices on solar penetration in a smart grid environment with distributed energy storage. *Appl. Energy* **2021**, *282*, 116168. <https://doi.org/10.1016/j.apenergy.2020.116168>.
39. Andoni, M.; Robu, V.; Couraud, B.; Fruh, W.-G.; Norbu, S.; Flynn, D. Analysis of Strategic Renewable Energy, Grid and Storage Capacity Investments via Stackelberg-Cournot Modelling. *IEEE Access* **2021**, *9*, 37752–37771. <https://doi.org/10.1109/access.2021.3062981>.
40. Zhang, Y.; Gu, C.; Yan, X.; Li, F. Cournot oligopoly game-based local energy trading considering renewable energy uncertainty costs. *Renew. Energy* **2020**, *159*, 1117–1127. <https://doi.org/10.1016/j.renene.2020.06.066>.
41. Arvidsson, R.; Svanström, M.; Sandén, B.A.; Thonemann, N.; Steubing, B.; Cucurachi, S. Terminology for future-oriented life cycle assessment: Review and recommendations. *Int. J. Life Cycle Assess.* **2023**, *29*, 607–613. <https://doi.org/10.1007/s11367-023-02265-8>.
42. To, W.M.; Lee, P.K.C. GHG emissions from electricity consumption: A case study of Hong Kong from 2002 to 2015 and trends to 2030. *J. Clean. Prod.* **2017**, *165*, 589–598. <https://doi.org/10.1016/j.jclepro.2017.07.181>.
43. Wang, W.; Luo, Y.; Zhao, D. The Power Transition under the Interaction of Different Systems—A Case Study of the Guangdong–Hong Kong–Macao Greater Bay Area. *Sustainability* **2023**, *15*, 5577. <https://doi.org/10.3390/su15065577>.
44. Ye, L.H.; Lu, L.; Zhang, S.H. A novel reliability-oriented assessment method for coastal urban region spatial resource and power yield analysis for offshore wind farms. *Energy Rep.* **2025**, *13*, 3121–3135. <https://doi.org/10.1016/j.egyr.2025.02.054>.
45. HKSAR. *The Scheme of Control Agreement Entered into by the Government of the Hong Kong Special Administrative Region and the Following Companies: CLP Power Hong Kong Limited and Castle Peak Power Company Limited*; HKSAR: Hong Kong, China, 2018.
46. CLP. *Tariff Table—Chinese (2022-01-01)*; CLP: Hong Kong, China, 2022.
47. CLP. *Tariff Table—English (2021-01-01)*; CLP: Hong Kong, China, 2021.
48. CSD. *General Tariff for Electricity, 2022–2023*; CSD: Hong Kong, China, 2024.
49. Abdin, Z.; Khalilpour, K.; Catchpole, K. Projecting the levelized cost of large scale hydrogen storage for stationary applications. *Energy Convers. Manag.* **2022**, *270*, 116241. <https://doi.org/10.1016/j.enconman.2022.116241>.
50. IEA. *Integrating Solar and Wind-Global Experience and Emerging Challenges*; IEA: Paris, France, 2024.
51. Cacciarelli, D.; Pinson, P.; Panagiotopoulos, F.; Dixon, D.; Blaxland, L. Do we actually understand the impact of renewables on electricity prices? A causal inference approach. *iEnergy* **2025**, *4*, 247–258. <https://doi.org/10.23919/ien.2025.0027>.
52. Lam, P.-L. Hong Kong's electricity market beyond 2008. *Energy Policy* **2004**, *32*, 851–854. <https://doi.org/10.1016/j.enpol.2003.08.007>.
53. Dunkle Werner, K.; Jarvis, S. Rate of return regulation revisited. *J. Public Econ.* **2026**, *259*, 105654. <https://doi.org/10.1016/j.jpubeco.2026.105654>.
54. Crowley, N.; Meitzen, M. Measuring the price impact of price-cap regulation among Canadian electricity distribution utilities. *Util. Policy* **2021**, *72*, 101275. <https://doi.org/10.1016/j.jup.2021.101275>.
55. Bachner, G.; Mayer, J.; Steininger, K.W. Costs or benefits? Assessing the economy-wide effects of the electricity sector's low carbon transition—The role of capital costs, divergent risk perceptions and premiums. *Energy Strategy Rev.* **2019**, *26*, 100373. <https://doi.org/10.1016/j.esr.2019.100373>.
56. Guven, D. Offshore wind-driven green hydrogen: Bridging environmental sustainability and economic viability. *Int. J. Hydrog. Energy* **2024**, *72*, 661–676. <https://doi.org/10.1016/j.ijhydene.2024.05.335>.
57. Meng, W.-C.; Yang, Z.-M.; Lin, X.; Yu, J.-Y.; Rao, Z.; Li, J.-Z.; Cao, Y.-W.; Jin, H.-Y.; Tang, H.-Y. Life Cycle Environmental Impact Assessment of Offshore Wind Power Combined with Hydrogen Energy Storage System. *Energies* **2025**, *18*, 6279. <https://doi.org/10.3390/en18236279>.
58. Ke, Y.M.; Tang, H.Y.; Liu, M.; Meng, Q.X.; Xiao, Y. Optimal sizing for wind-photovoltaic-hydrogen storage integrated energy system under intuitionistic fuzzy environment. *Int. J. Hydrog. Energy* **2023**, *48*, 34193–34209. <https://doi.org/10.1016/j.ijhydene.2023.05.245>.
59. Yang, M.; Wang, D.; Zhang, W. A novel ultra short-term wind power prediction model based on double model coordination switching mechanism. *Energy* **2024**, *289*, 130075. <https://doi.org/10.1016/j.energy.2023.130075>.
60. Pierri, E.; Binder, O.; Hemdan, N.G.A.; Kurrat, M. Challenges and opportunities for a European HVDC grid. *Renew Sust Energy Rev* **2017**, *70*, 427–456. <https://doi.org/10.1016/j.rser.2016.11.233>.

61. Kaur, R.; Gera, P.; Jha, M.K.; Bhaskar, T. Thermochemical Route for Biohydrogen Production. In *Biohydrogen*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 187–218.
62. Haseli, Y. Maximum conversion efficiency of hydrogen fuel cells. *Int. J. Hydrog. Energy* **2018**, *43*, 9015–9021. <https://doi.org/10.1016/j.ijhydene.2018.03.076>.
63. Andersson, J.; Grönkvist, S. Large-scale storage of hydrogen. *Int. J. Hydrog. Energy* **2019**, *44*, 11901–11919. <https://doi.org/10.1016/j.ijhydene.2019.03.063>.
64. Ferreira, A.P.R.A.; Oliveira, R.C.P.; Mateus, M.M.; Santos, D.M.F. A Review of the Use of Electrolytic Cells for Energy and Environmental Applications. *Energies* **2023**, *16*, 1593. <https://doi.org/10.3390/en16041593>.
65. Salameh, Z. Energy Storage. In *Renewable Energy System Design*; Elsevier: Amsterdam, The Netherlands, 2014; pp. 201–298.
66. Suppes, G.J.; Storvick, T.S. Energy Conversion and Storage. In *Sustainable Power Technologies and Infrastructure*; Academic Press: Cambridge, MA, USA, 2016; pp. 121–159.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.