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The application of green innovation to technological innovation in building a low-carbon economic system

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SUMMARY: *The path to a low-carbon economy is an essential route for cities to become smart. This paper first analyzes the relevant applications of smart transportation, smart energy, and smart waste management systems within the low-carbon economy. Addressing the challenge of low energy efficiency utilization in cities, this paper proposes a dual-layer ADN scenario planning model to promote efficient energy use. It first establishes a fundamental framework for ADN planning within a low-carbon economic system. Recognizing the nonlinear dual-layer mixed-integer programming characteristics of the ADN planning model, it employs the Cuckoo Search algorithm—known for its strong global search capability—and the fast, efficient primal-dual interior point method to solve the upper and lower sub-layers of the model, respectively. Experimental results demonstrate that compared to models like PWL-MILP and SO-WGA, the ADN planning model reduces emission costs by 40.44% in both active distribution network operation and DHN independent operation scenarios, yielding resource allocation schemes with the lowest total configuration costs. In the development of wind power, photovoltaics, and energy storage in Province X, the AND planning model can rapidly increase photovoltaic penetration rates and power generation capacity while reducing photovoltaic costs, providing a feasible green innovation approach for regional low-carbon energy transition.*

KEYWORDS: *ADN planning; Cuckoo Search Algorithm; Primitive Dual Interior Point Method; Low-Carbon Economic System*

1 Introduction

Climate change is now one of the most serious problems that are affecting humanity across the globe in the contemporary world [1]. Climate change is highlighted by Feulner, G [2] as humanity's biggest challenge of the 21st century. Human intervention in the climate system has caused global average temperatures and annual mean temperatures to rise by approximately 0.8 degrees Celsius since the 19th century. Glacial melting, rising sea levels, and frequent extreme weather events all warn us that Earth's ecological environment is in a precarious state [3, 4]. Faced with such a severe situation, a low-carbon economic system driven by green innovation is now imperative [5].

On the path to developing a low-carbon economy, energy technology innovation is a crucial step [6]. Dongyang, L [7] examined the drivers of technological progress on the path to green, low-carbon development. Using an empirical model-based methodology, the study demonstrated that innovative technologies can significantly reduce carbon emissions and promote the expansion and deepening of green, low-carbon economic transformation pathways. Traditional energy sources, such as coal and oil, while bringing tremendous progress to human

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society, have also triggered a series of environmental issues, including global warming caused by greenhouse gas emissions [8, 9]. As pointed out by Ahove, M. and Bankole, S. [10], the introduction of petroleum resources has contributed significantly to human living standards. Nevertheless, the petroleum industry operations and unsustainable consumption behaviors have also led to the emission of greenhouse gases that cause several problems of climate change. There are several technological innovations to deal with this situation.

Solar photovoltaic power generation technology has made enormous advances over the last several years [11]. The efficiency of solar cells has been greatly improved through sustained research and development of new photovoltaic materials and improved cell designs, whereas the costs have been steadily reduced [12, 13]. Solar photovoltaic (PV) and concentrated solar power (CSP) technologies were reviewed by Khan, J. and Arsalan, M. [14], who discussed the types, efficiencies, and costs of these technologies. Their results suggest that PV is more commercialized and advanced than CSP that provides greater economic benefits. Historically, solar PV power generation was too expensive to be widely adopted [15]. Nevertheless, innovations in technology have already allowed the cost of solar PV to become comparable to fossil-fuel-based energy generation in certain areas [16, 17]. This transition is changing solar energy as an additional power source to a main energy carrier and significantly decreasing reliance on conventional fossil fuels, reducing carbon emissions and developing a low carbon economy [18, 19].

The low-carbon economic development pathways of China were presented by Yang, W et al. [20] through various aspects such as energy, low-carbon technologies, and carbon emission reduction goals. They observed that despite the successful implementation of low-carbon policies, there are still some challenges, and they made suggestions to the low-carbon economic development of China. Tian, L et al. [21] stressed that low-carbon economy and energy savings and environmental protection are important issues of modern and future socioeconomic progress. The authors specified the benefits of combining photovoltaic power generation with rail transit power supply systems, such as low operating expenses, minimization of carbon emissions, and popularization of new energy applications.

Technology related to the generation of wind power has also developed quickly. Since the initial small wind turbines up until the current large wind turbine generators with high efficiencies, the capacity of individual units has continued to grow whereas the power generation efficiency has improved greatly [22, 23].

B. Desalegn, et al. [24] observed that engineers are trying to optimize WECS performance to obtain maximum wind energy at minimum cost. The authors evaluated energy harvesting performance of WECS technology, its cost-effective features, and design improvements. Moreover, offshore wind power technology is much more developed. There are abundant offshore wind resources allowing the construction of wind farms to harvest more wind energy, which can supply large volumes of clean electricity to coastal areas [25-27]. The present situation, future aspects, and technical issues of offshore wind farms were listed by Díaz and Soares [28]. Their study discussed the development of offshore wind technologies associated with the pre-construction and existing projects, summarizing the conclusions with the discussion on the future design and capacity of the offshore wind farms. Zhang, J., and Wang, H. [29] have used the published information, data, and other online sources to talk about the history of the development of offshore wind power generation and offshore wind turbine foundations in China, showing the types of foundations used by the example of an offshore wind farm project. Technological innovations have significantly enhanced the stability and reliability of wind power generation, addressing historical challenges of intermittency and variability. This enables better grid integration, positioning wind power as a vital component in building low-carbon economic systems [30-33]. Zhang, R et al. [34] proposed an adjustable robust power dispatch model for low-carbon economies based on wind power uncertainty, validating its effectiveness in reducing carbon emissions and curtailed wind power. Overall costs decrease as the number of carbon capture power plants increases. Parkinson, S. et al. [35] outlined the opportunities and challenges faced by power system operators in mitigating the negative impacts of wind power integration. They analyzed the potential for traditional passive loads to play an active role in resources that counteract wind variability.

This paper aims to construct a renewable energy planning model oriented toward low-carbon objectives. It first defines the concepts of low-carbon economy and green innovation, systematically analyzes the current application status of green technological innovation in areas such as smart transportation, and subsequently proposes a two-layer ADN scenario planning model. The upper layer of the model implements investment decisions, while the lower layer performs operational simulations. A hybrid algorithm combining the Cuckoo Search algorithm and the primal-dual interior point method is employed for model solution. Finally, performance comparison tests were conducted using a 13-node DHN system and an extended IEEE-33 node test system. Case studies validate the model's effectiveness in facilitating green transitions across diverse energy development scenarios.

2 Green Technology Innovation in a Low-Carbon Economic System

2.1 Conceptual Definitions

2.1.1 Low-Carbon Economy

A low-carbon economy is an economic model centered on reducing greenhouse gas emissions—particularly carbon dioxide emissions. It represents a new economic development paradigm that decouples economic growth from carbon emissions through technological innovation, industrial transformation, energy structure adjustment, and institutional optimization. Its core philosophy lies in advancing socioeconomic sustainability by enhancing energy efficiency, developing clean energy, promoting low-carbon technologies, optimizing industrial structures, and advocating low-carbon lifestyles. This approach significantly reduces dependence on fossil fuels and curtails high-carbon activities. The effective advancement of this economic model requires collaborative efforts among governments, enterprises, and all sectors of society to foster technological innovation, strengthen policy support, and raise public awareness, thereby building a cleaner, greener, and more sustainable economic system. As a solution to global climate change, the low-carbon economy has become the mainstream direction for global economic development.

2.1.2 Green Innovation

The concept of green technological innovation posits that it refers to the innovation of technologies, processes, and products aimed at protecting the ecological environment, reducing environmental pollution, and conserving raw materials. As the importance of environmental sustainability continues to grow, green technological innovation is gaining widespread attention and recognition. It has the potential to enhance total factor carbon productivity through mitigation effects, thereby improving energy efficiency. Green technological innovation serves as a key driver for advancing high-quality economic and social development. Clarifying the transmission mechanism of its performance outcomes is essential for effectively promoting innovation activities. The essence of green technological innovation lies in organizing and transforming environmental systems. It emphasizes technological design, improvement, and innovation in products, materials, and equipment to enhance environmental sustainability. By achieving energy conservation and emission reduction through structural adjustments and energy substitution, green technological innovation remains a critical factor in modern environmental governance.

2.2 Application of Green Technology Innovation

2.2.1 Smart Low-Carbon Transportation

The aim of smart transportation development is to actually ensure intelligent, low-carbon, green, and convenient travel. It seeks to minimize energy usage in commutes, and it is also aimed at reducing traffic congestion and road safety concerns when trying to optimize travel patterns and improve transportation efficiency. The main approach to low-carbon smart transportation is to develop a green transportation network system of urban public transit, walkways and cycle paths. This system regulates and limits the use of cars that are not reasonable and encourages non-polluting forms of transport including public transit, bicycles and walking. It provides holistic and multi-dimensional travel services to the public through harnessing sensor and communication technologies to enable them achieve seamless connectivity. Other countries across the world have also adopted very efficient measures to get this task done.

Smart transportation systems in public transportation services allow citizens to see arrival times at any time and place using a mobile device such as a smartphone, which helps them plan their trips. The passengers may also buy tickets using text messages or applications, which save time and distance of traveling, decrease traffic congestion, and provide comfortable trips. More use of public transit eventually will be beneficial to the environment of the city due to low carbon sustainable development.

2.2.2 Smart Low-Carbon Energy

The essence of urban low-carbon economies is based on the transformation of energy structures and improving the efficiency of energy usage. The mass introduction of smart energy systems contributes to this aim and is one of the most important foundations and the essential necessity of smart cities. Electricity and internal combustion engines were the catalysts of the Second Industrial Revolution and smart grids are an important part of smart energy systems. Smart grids are characterized by distributed energy and involve high energy efficiency utilization and low negative environmental impact. In one aspect, it uses combined cooling, heating, and power (CCHP) and combined heat and power (CHP) technologies to provide efficient cascading energy use. Through increasing energy efficiency, it can achieve more output with the same amount of energy consumed, which results in decreasing the greenhouse gases emitted. Conversely, distributed energy engages and interacts with renewable sources. Distributed photovoltaic systems, distributed wind power systems, and fuel cells have less environmental effects and play a major role in enhancing environmental quality and energy saving.

The smart grids successfully combine advanced technologies such as sensing and measurement, automation, and intelligent control with the traditional power grids, thus allowing operational processes to become measurable, controllable, and automated. The smart grids help in the integration and management of a variety of alternative energy sources that can be used in different types of generation and storage of electric power. With respect to management, users monitor electrical equipment with communication systems, which are connected into the smart grid information systems to offer updates on time. User and grid roles can be transmuted into each other by closely connecting them both.

The development of smart energy systems can allow the implementation of smart monitoring, intelligent inspections, automated diagnostics, automatic alerts, and customized power solutions. The security of urban energy systems can be achieved through the use of clean energy generation, energy storage systems, and energy efficiency management platforms. This strategy raises the share of clean energy, eliminates energy waste, and facilitates a low-carbon, green, and livable development in the city.

2.2.3 Smart Low-Carbon Waste Management System

The smart processing model is implemented in the spatial framework of urban communities and the principle of distributed processing. The model combines contemporary information technologies including the Internet of things (IoT) and low-carbon technologies of processing to integrate waste collection, transportation, treatment, and control. As it correctly indicates the state of every stage in the waste management system with the help of data, it can regulate the whole process in real time. This solution corresponds to the requirements of urban garbage collection and treatment services with lower energy consumption of the system as a whole and higher quality of municipal waste management.

Smart processing model integrates smart sorting, smart treatment and smart control processes. Smart sorting system improves the effectiveness of waste classification at the smart sorting stage. In smart processing, solar-powered biochemical treatment is used to convert organic waste into organic compound fertilizer, biogas, and residual ashes. Carbonization technology converts inorganic waste into biochar, flammable gas and low levels of tar residues. Waste with high calorific values are combusted to produce energy which is directly supplied to the city energy network which is more efficient in terms of conversion and energy usage. Gasification treatment is applied to hazardous waste to decompose and reorganize waste composition so that waste can be turned into useful resources. Remaining residual materials are safely disposed of using controlled landfill methods, so that safe end-of-life disposal is achieved and the safety and carbon-neutral character of waste management in the cities is ensured. Intelligent control systems are incorporated into all steps of the smart processing process. These systems utilize contemporary technologies such as the Internet of Things (IoT) and cloud computing to optimize and regulate sorting, transportation, and processing processes, balancing the amount of waste generated with the amount of waste treatment capacity available.

2.3 Proactive Planning to Promote Energy Efficiency

In the process of advancing a low-carbon economic system through green innovation, the key to applying technological innovation lies in achieving significant improvements in energy utilization efficiency. This paper explores application methods for green technological innovation using proactive planning approaches that promote efficient energy use as an example, thereby enabling the transformation of energy systems from passive response to active intervention.

2.3.1 Basic Framework for ADN Planning

The basic framework of ADN planning for promoting efficient renewable energy utilization is illustrated in Figure 1. In the diagram below, white modules represent the fundamental components of traditional distribution network planning, gray modules denote additional considerations introduced by MG planning on this foundation, while green modules signify distinctive features further incorporated into the ADN planning model proposed in this paper. Evidently, compared to traditional distribution networks or MGs, ADN planning under a low-carbon context exhibits significant expansion in both framework structure and model content.

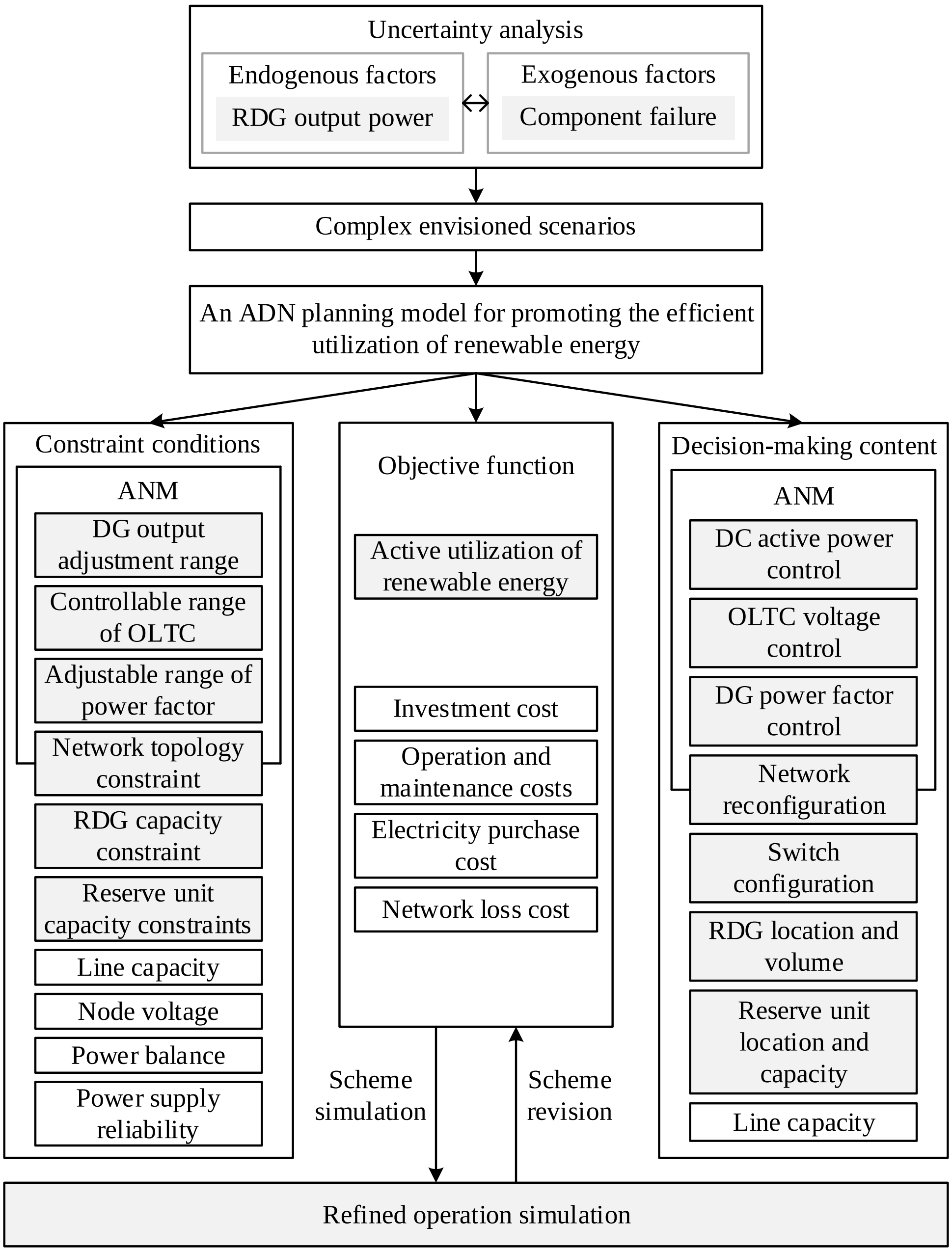


Figure 1: Basic framework of ADN planning

First, the optimization objective for the active integration of renewable energy with diversified characteristics requires comprehensive consideration of factors such as the system's investment, operational economics, and low-carbon benefits. Simultaneously, the incorporation of ANM significantly expands the scope of decision-making within the model, while ANM's inherent properties introduce additional constraints to the optimization process. Moreover, ADN planning decisions must account not only for inherent uncertainties like RDG performance and electricity demand but also for the impact of exogenous factors such as line failures on the actual contribution of RDG efficiency. This alters the feasible optimization space while necessitating the consideration of complex operational scenarios and detailed simulations during the planning phase. Traditional planning approaches that neglect operational aspects are no longer applicable. Thus, ADN planning under low-carbon conditions clearly exhibits heightened complexity and research challenges.

2.3.2 ADN Dual-Layer Scenario Planning Model

As mentioned above, ADN planning requires building upon traditional distribution network planning by further considering the control potential of ANM. Under constraints related to safe operation, it aims to achieve the comprehensive optimal balance between system economic efficiency and renewable energy utilization. Economic efficiency serves as the foundational objective, while the latter represents an additional, expanded requirement imposed by ADN's green and low-carbon principles on planning and design. These two objectives are deeply coupled yet inherently contradictory, exhibiting distinct hierarchical differences in practical implementation. Conventional modeling approaches struggle to accurately capture such multi-level hierarchical logic structures in planning problems. Therefore, this paper applies dual-layer planning theory to incorporate the goal of promoting efficient renewable energy utilization as a constraint within the economic objective function of distribution network planning. The resulting ADN dual-layer scenario planning model is constructed as follows:

$$
\begin{aligned}
&\min F(\tau_{ij,a},\varsigma_{ij},n_g^{rdg},n_g^r)\\
&s.t.\begin{cases}
G(n_g^{rdg},n_g^r)\le 0\\
\tau_{ij,a},\varsigma_{ij}\in[0,1]\\
\max f(P^{gsp},P_g^{rdg},P_g^r,T^{olic},P_g^{rH},\varphi_g)\\
b(P^{gsp},P_g^{rdg},P_g^r,P_g^{crl},\varphi_g)=0\\
g(P^{gsp},P_g^{rdg},P_g^r,T^{olic},P_g^{crl},\varphi_g)\le 0
\end{cases}
\end{aligned}
\tag{1}
$$

In the equation, $F(\cdot)$ and $f(\cdot)$ represent the objective functions of the upper and lower submodels, respectively, corresponding to the optimization goals of investment economics and promoting efficient renewable energy utilization in this paper. $\tau_{ij,a},\varsigma_{ij},n_c^{rds}$ and n_g^r are decision variables of the upper submodel, representing the expansion conductor type, switch installation, and the installation location and capacity of RDG and rotating reserve units, respectively. Among these, $\tau_{ij,a}$ and ς_{ij} are discrete 0-1 Boolean variables. $P^{gsp},P_s^{rds},P_g^r,T^{OLTC},P_s^{ct}$ and φ_g are decision variables of the lower-level submodel, representing the optimal power values obtained by ADN from the upper-level grid, RDG, and spinning reserve, as well as the optimal control parameters of ANM, including OLTC position, RDG power reduction value, and its power factor. Additionally, $G(\cdot)$ and $g(\cdot)$ represent the inequality constraint sets for the upper and lower levels, respectively; $b(\cdot)$ is the equality constraint set for the lower level.

2.3.3 Hybrid Solution Algorithm

The aforementioned model essentially constitutes a nonlinear two-layer mixed-integer programming problem. The upper layer involves an integer optimization problem for DG siting, capacity allocation, and grid structure planning, while the lower layer addresses an optimal power flow (OPF) problem incorporating continuous decision variables [36].

Given the model's characteristics, this paper employs a hybrid cuckoo search algorithm [37] for solution. Its fundamental approach is as follows: leveraging the strong global search capability of cuckoo search (CS) as the primary tool for solving the upper-layer main problem. For the large number of feasible planning schemes generated, the fast and efficient primal-dual interior point method (PDIPM) [38] is then applied to solve the lower-layer subproblem. The specific solution process is as follows:

1) Algorithm parameter initialization. Includes: Number of available host nests n; Host discovery probability p_a; Step size control α; Search accuracy ϕ; and Maximum search iterations $T_{\max}$.

2) Determine the required dimensional space for a single host nest based on the number of line corridors, network switches, RDGs, and rotating reserve candidate nodes in the system. Each candidate planning scheme corresponds to a host nest in the CS scheme library, encoded using integer values representing the selected line type, switch installation status, RDG configuration, and reserve unit capacity in the system. Randomly generate n feasible nest locations.

3) Calculate and record the investment costs corresponding to each entity, and input them as known parameters into the lower-level submodel.

4) First, use PDIPM to compute the system's optimal power flow under normal operating conditions for each planning scenario, thereby determining the network operating state scenario set Ω_s.

5) Building upon step 4), further compute the optimal power flow under complex anticipated scenario (s, ss') (accounting for network faults) using PDIPM. Feed the results back to the upper-level model to calculate the expected system cost during the operational phase and the upper-level objective function value $F(\cdot)$.

6) Calculate the fitness values J for each Bird's Nest individual in the current generation using the linear ranking method, then sort them in descending order.

$$J(\vartheta) = 2 - \eta + 2(\eta - 1) \cdot \frac{(x_h - 1)}{(HMS - 1)} \tag{2}$$

In the formula, η represents the adjustment coefficient; x_h denotes the position of an individual after sorting by the upper-layer objective function value; HMS indicates the number of model constraints.

7) Compare the above nest individual with the individual of lowest fitness value in the previous generation. If $J(\vartheta^{new}) > J(\vartheta^{old})$ holds, replace the inferior nest in the previous generation set with the superior nest and update the current nest set.

8) Determine if the maximum search iteration count of $T_{\max}$ has been reached. If so, output the nest at the current optimal position as the final planning solution. Otherwise, perform nest position updates, host identification, and evaluation selection according to CS rules to generate a new generation of nests, then return to step 3).

The computational flow of the above algorithm is illustrated in Figure 2.

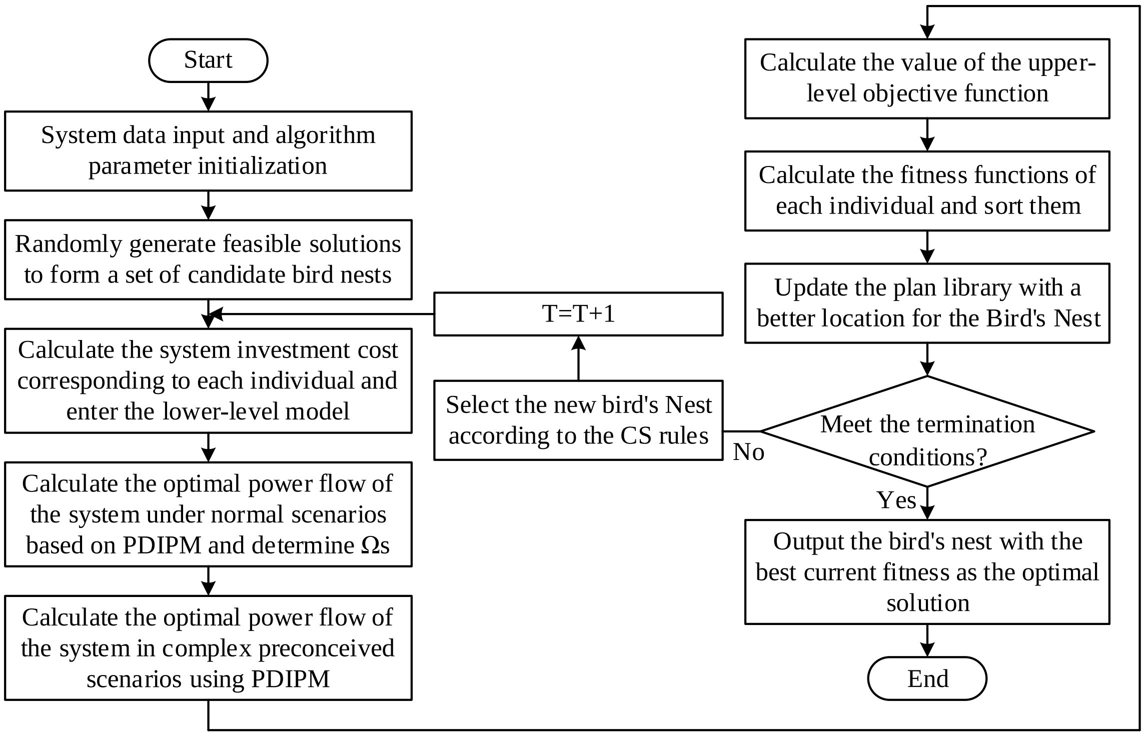


Figure 2: Flowchart of the calculation of the hybrid solution algorithm

3 ADN Dual-Layer Scenario Planning Model and Its Algorithm Analysis

3.1 Simulation Experiment Testing System

This paper validates the model's performance through simulation experiments based on a 13-node DHN system and an extended IEEE-33 node test system design. Two sets of DHN systems are integrated into the active distribution network. Additionally, three scenarios are designed according to the optimized configuration of the EHIES. Scenario 1: Active distribution network operation with standalone DHN operation, without integrating energy storage (ESS) or grid-connected batteries (GB) into the DHN. Scenario 2: Optimized configuration of DHN equipment only, with DHN devices randomly integrated into active distribution network operation. Scenario 3: Fully optimized configuration of EHIES, with ESS integrated into operation on the active distribution network side.

This paper employs an ADN planning model to optimize the configuration of equipment within an EHIES. Under identical test conditions, the traditional piecewise linearized MILP model (PWL-MILP) and the single-objective linear weighted GA scheduling model (SO-WGA) serve as comparative models to validate the superiority of the ADN planning model in addressing EHIES configuration optimization. All computational examples are executed on the MATLAB 2023a platform. Furthermore, the simulation assumes instantaneous transfer of thermal and electrical energy, with no additional losses beyond those explicitly included in the model.

3.2 Performance Analysis of the AND Planning Model

Figure 3 shows the optimized daily average heating temperature curve of the DHN. Figure 4 presents the average voltage curves at active distribution network nodes obtained by different algorithms under three scenarios, with (a), (b), and (c) representing the curves for the ADN planning model, SO-WGA, and PWL-MILP model, respectively. Table 1 lists the optimization results for Scenario 3. Combining the data from Figures 3 and 4 with Table 1 reveals that the PWL-MILP model achieves the lowest total configuration cost for the EHIES. However, it exhibits the highest heating temperature fluctuation, increasing by 28.55% compared to the initial state in Scenario 1, which is clearly undesirable. Compared to Scenario 1, the ADN planning model reduces heating temperature fluctuation by 9.12%, active distribution network voltage fluctuation by 53.12%, and emission costs by 40.44%. In contrast, the SO-WGA model exhibits higher total configuration costs, heating temperature fluctuation, active distribution network voltage fluctuation, and emission costs than the ADN planning model. The curves in Figures 5(a) and 5(b) indicate that the ADN planning model exhibits smaller average node voltage fluctuations, with values closer to 1.0 percentage point (p.u.). This demonstrates superior optimization performance of the ADN planning model.

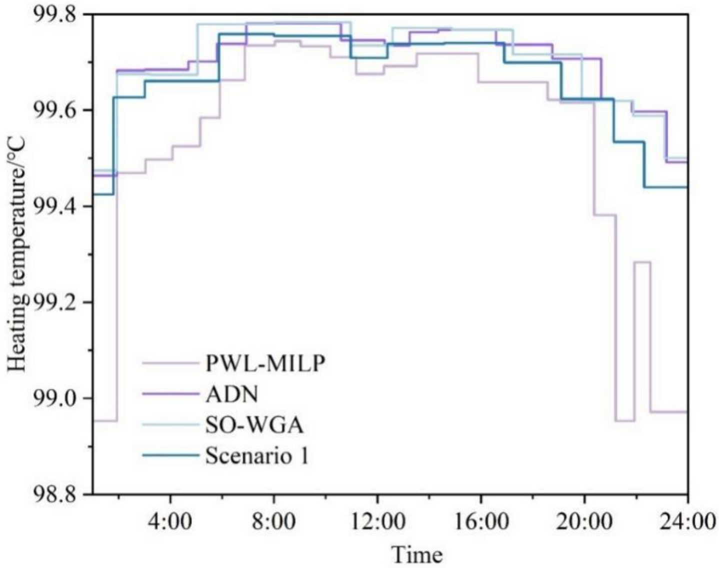
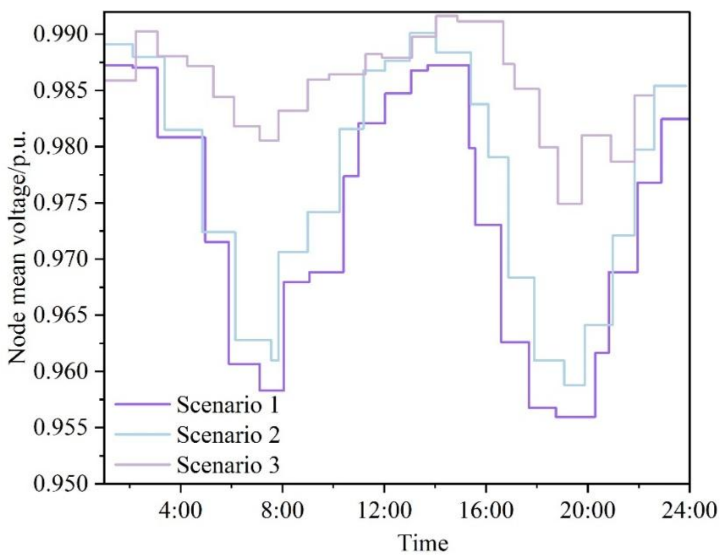
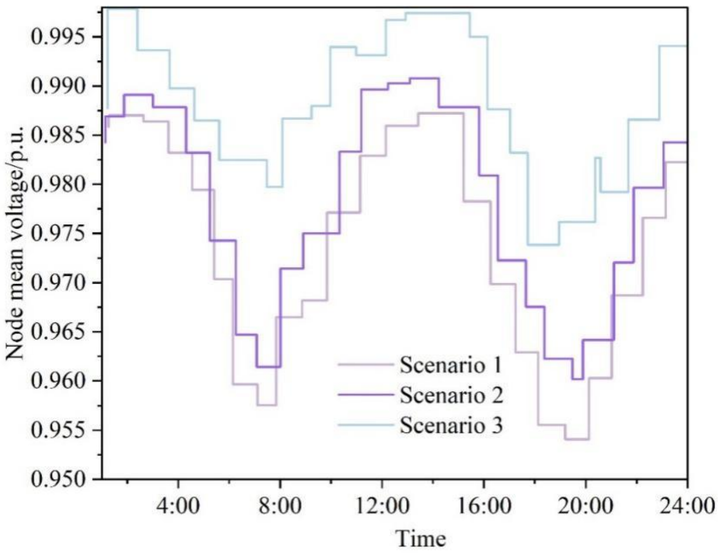


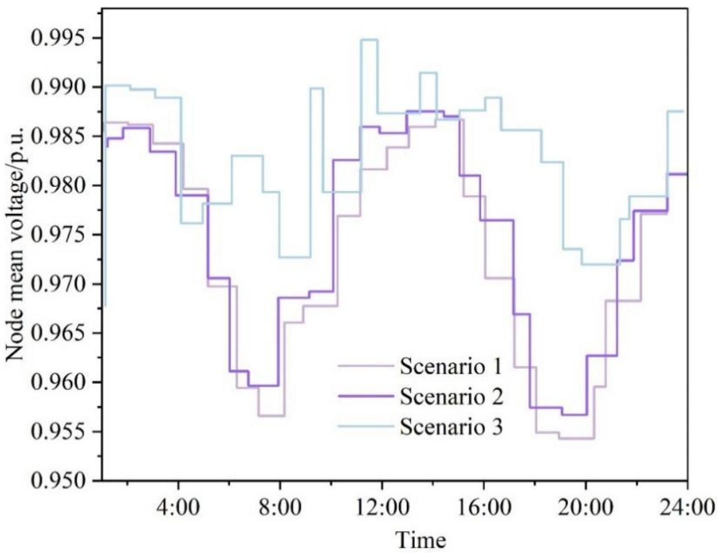
Figure 3: DHN daily average heating temperature curve



(a)ADN



(b)SO-WGA



(c)PWL-MILP

Figure 4: The average voltage curve obtained by different algorithms

Table 1: Scenario 3 optimization results

Algorithm	Target function			Discharge cost/(yuan per day)	The cost of emissions is over /%
	Total allocation cost/(yuan/day)	Heat temperature fluctuations/(°C/day)	Voltage fluctuation /(p.u./ day)		
ADN	400585.20	7.050	0.158	28800	7.19
PWL-MILP	300156.25	10.541	0.226	24500	8.16
SO-WGA	467890.58	7.195	0.231	31500	6.73

4 Case Studies on Innovative Applications of Planning Models

4.1 Pareto Non-Dominance Surface Analysis

Plotting the optimized solution set obtained from the AND planning model in a three-dimensional coordinate system yields the Pareto non-dominated surface. The Pareto non-dominated surface of the AND planning model is shown in Figure 5. As mentioned earlier, solving multi-objective optimization problems requires satisfying two fundamental conditions. The figure demonstrates that all individuals in the final generation are distributed close to the Pareto frontier, indicating excellent convergence that satisfies the convergence requirement for solving multi-objective problems. Second, the non-dominated solutions are uniformly and sparsely distributed along the three indicator directions of cumulative cost, cumulative carbon emissions, and cumulative excess power generation, satisfying the diversity requirement for multi-objective problem solutions. The final generation did not get stuck in a local optimum, ensuring the diversity of non-dominated solutions. This facilitates the exploration of diverse energy development pathways during the operational phase of the ADN two-layer scenario planning model for Province X.

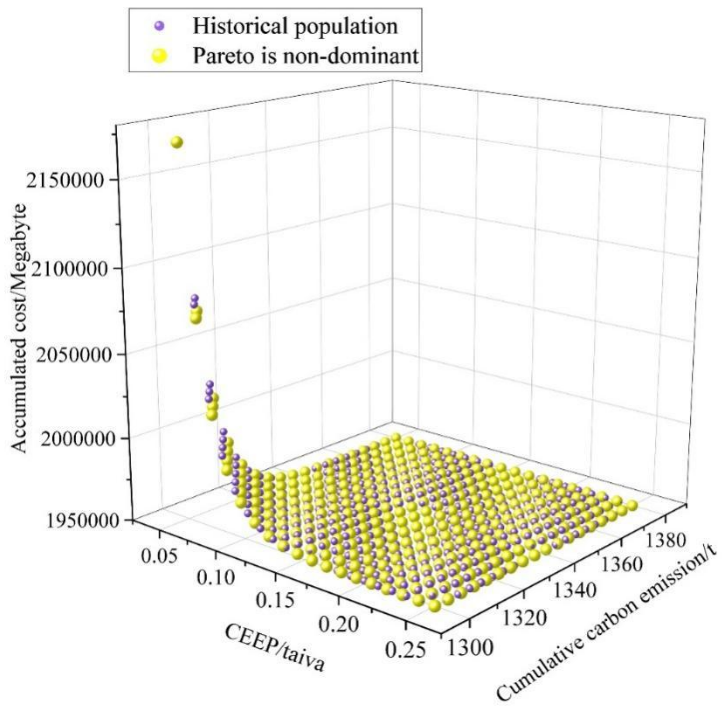


Figure 5: Energy development optimization pareto front surface

4.2 Analysis of Wind Power Development

Figure 6 shows the installed capacity changes for wind power across all energy scenarios during the operational period of the ADN two-layer scenario planning model in Province X. It can be observed that most scenarios predict significantly higher growth in wind power capacity between 2020 and 2021 compared to the period from 2021 to 2024. This indicates that the planning model tends to rapidly increase wind power capacity and grid connection during the early planning phase. This is primarily because wind power projects have an average construction cycle of one year, which is shorter than the 1-2 year construction cycle for coalfired power plants, enabling faster expansion of power generation capacity in the short term.

Secondly, as the impact of the pandemic gradually subsides, X Province's economic growth continues to accelerate, driving further increases in electricity demand. In 2021, the province's total electricity consumption is projected to rise by approximately 12% compared to 2020. X Province's characteristic of experiencing wind and rain simultaneously will significantly boost wind power generation. Furthermore, the rapid expansion of energy storage installations will effectively ensure grid stability and reduce curtailment of wind power. It is foreseeable that wind power will become a robust guarantee for electricity supply during the operational period of the ADN dual-layer scenario planning model in Province X, providing momentum for economic growth.

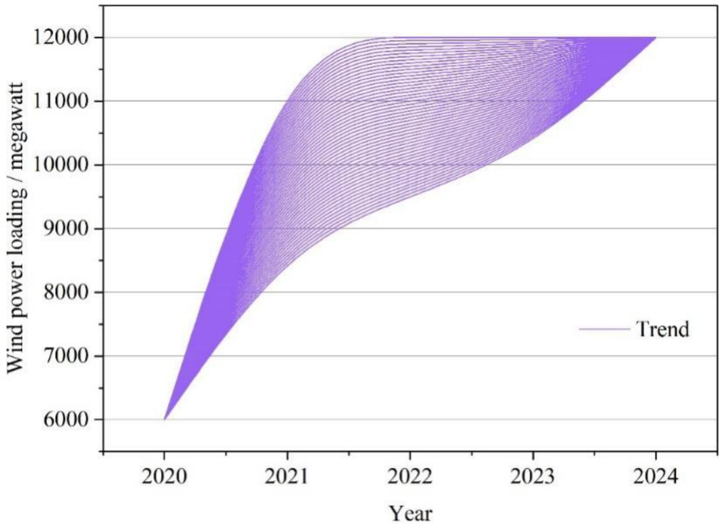


Figure 6: Wind power installation trend

Figure 7 shows the carbon intensity distribution of 400 alternative scenarios, sorted by increasing wind power capacity additions from 2020 to 2021. Observing the overall trend in the concentrated distribution areas reveals that the lowest cumulative carbon emissions occur when the first-year capacity additions are around 3,200 megawatts. Both excessively slow and excessively rapid capacity expansion lead to a significant increase in carbon emission intensity.

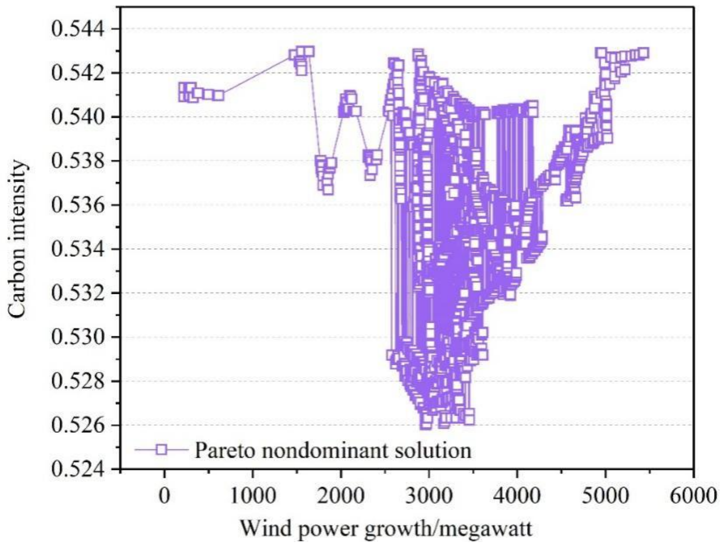


Figure 7: Carbon intensity distribution of alternative schemes

4.3 Analysis of Photovoltaic Development

Figure 8 shows the changes in photovoltaic installed capacity across all energy scenarios during the operational period of the ADN two-layer scenario planning model in Province X. It can be observed that most scenarios tend to achieve the planned installed capacity target by 2021, indicating that the optimization model favors rapidly increasing PV penetration in the short term. This is primarily because PV power plants can be operational within 3-4 months at the fastest, featuring a short construction cycle. They can quickly feed electricity into the grid to meet the rapidly growing electricity demand during the operational period of the ADN dual-layer scenario planning model in Province X. Secondly, due to the intermittent nature of PV output, sufficient generation capacity must be compensated for through increased installed capacity. After years of subsidy policies in Province X, PV generation costs have declined to a price range competitive with traditional energy sources. The related industrial chain has matured and become well-established, enabling rapid construction and return on investment. Therefore, PV generation will become the primary direction for expanding Province X's energy system during the operational period of the ADN dual-layer scenario planning model.

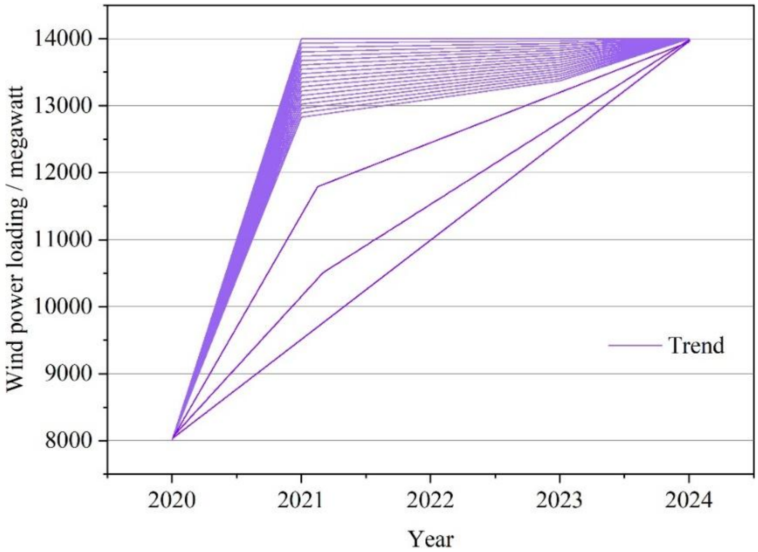


Figure 8: Photovoltaic change

Figure 9 illustrates the relationship between the first-year increase in PV installed capacity and cumulative costs. The trend line indicates that cumulative costs are directly proportional to the first-year increase in PV capacity, meaning more aggressive PV deployment plans can lead to significantly higher costs. This primarily stems from the rapid decline in PV costs. According to projections by the China New Energy Research Institute, PV costs are expected to decrease by over 50% in the next decade. Consequently, during the operational period of the ADN dual-layer scenario planning model (2020-2024), PV costs will experience a notable reduction. Therefore, a relatively delayed PV construction plan can effectively curb cost escalation. However, considering the intermittency of PV output, the PV installation schedule must still be aligned with the deployment of energy storage facilities.

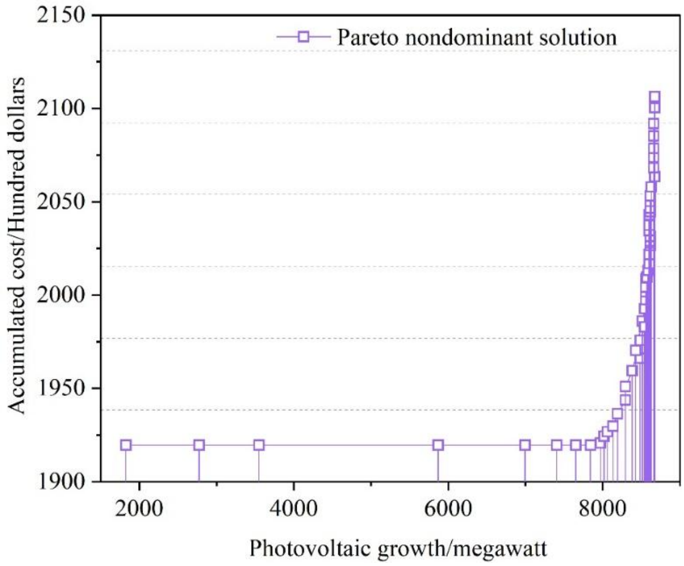


Figure 9: Loading increase and cumulative cost relationship

4.4 Energy Storage Development Analysis

Figure 10 shows the installed capacity changes of energy storage power stations across all energy scenarios during the operational period of the ADN two-layer scenario planning model in Province X. It can be observed that the increase in energy storage capacity during the first year is concentrated around 1,650 MW, indicating that the optimization model tends to schedule the construction of energy storage power stations at a steady pace, aligning them more closely with the expansion of photovoltaic and wind power. This is primarily because photovoltaic and wind energy are susceptible to external conditions such as weather, resulting in significant randomness and volatility in their output, which is detrimental to grid stability. Without other actions, restricting wind and solar production is the only choice to decrease generation, which inevitably leads to waste of resources. Energy storage facilities may supplement renewable generation with well-coordinated charging and discharging, which will effectively flatten output curves to achieve self-consumption. Consequently, the increase in energy storage capacity should be diverse and flexible to enable it to respond to the changing wind and solar construction plans.

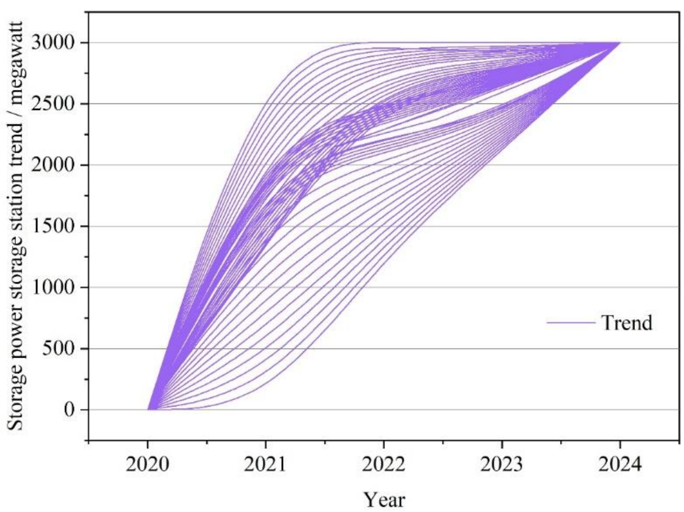


Figure 10: The installation change of energy storage plants

Figure 11 shows the correlation between annual energy storage power plant capacity growth and excess generation. As can be seen on the figure, the distribution of individual points is quite concentrated, which means that when energy storage construction plans are implemented, the Capacity Excess Energy Price (CEEP) will be reduced over time. At around 1,200 megawatts of energy storage capacity in the first year, the CEEP will be at its lowest level. After that point the impact on the improvement of the capacity of the system to absorb more power becomes insignificant. The main reason is the overambitious construction plans. Most companies, without properly evaluating the real needs of the system regarding energy storage, are rushing to tender projects to achieve policy goals without conducting any real construction. This leads to delays in grid connection for energy storage projects. Currently, energy storage projects still lack mature business models and viable market operation mechanisms. Economic factors constrain the actual deployment progress. Therefore, decision-makers need to thoroughly evaluate the actual energy storage demand of the power system in Province X to formulate construction plans.

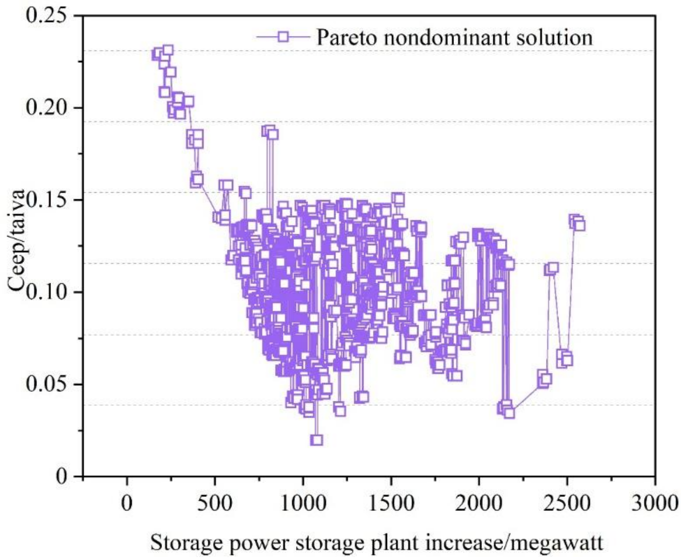


Figure 11: Installed growth and excess power generation

5 Conclusion

This paper proposes a dual-layer AND scenario planning model to promote energy efficiency under a low-carbon economic system.

Compared with PWL-MILP and SO-WGA, the AND planning model achieves optimal resource allocation for the EHIES. Scenario 3, optimized by the AND model, reduces emission costs by 40.44% compared to Scenario 1, decreases heating temperature fluctuations by 9.12%, and lowers voltage fluctuations in the active distribution grid by 53.12%. It also yields a more suitable total configuration cost.

The analysis examines the overall development trends of wind power, photovoltaic power, and energy storage during the implementation period (2020–2024) of the ADN two-layer scenario planning model in Province X. The increase in wind power capacity from 2020 to 2021 was significantly higher than that from 2021 to 2024, enabling Province X to rapidly expand its power generation capacity within a short timeframe. The ADN planning model also facilitates a swift rise in PV penetration while simultaneously reducing PV costs. The growth of installations of energy storage fluctuated about 1,650 MW between 2020-2021 with the implication that the AND planning model can plan the construction of storage plants on an even basis and hence contribute to wind and solar development. The intelligent use of the ADN two-layer situation planning model in Province X is an assurance to the progress of renewable energy in Hunan Province and helps establish a viable and efficient low-carbon economic system.

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