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Artificial Intelligence-Driven Multi-Energy Optimization: Promoting Green Transition of Rural Energy Planning and Sustainable Energy Economy

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Abstract: This research contributes to the overarching objectives of achieving carbon neutrality and enhancing environmental governance by examining the role of artificial intelligence-enhanced multi-energy optimization in rural energy planning within the broader context of a sustainable energy economy. By proposing an innovative planning framework that accounts for geographical and economic disparities across rural regions, this study specifically targets the optimization of energy systems in X County of Yantai City, Y County of Luoyang City, and Z County of Lanzhou City. Furthermore, it establishes a foundation for integrating these localized approaches into broader national carbon-neutral efforts and assessments of green total factor productivity. The comparative analysis of energy demand, conservation, efficiency, and economic metrics among these counties underscores the potential of tailored solutions to significantly advance low-carbon practices in agriculture, urban development, and industry. Additionally, the insights derived from this study offer a deeper understanding of the dynamics between government and enterprise in environmental governance, empirically supporting the Porter hypothesis, which postulates that stringent environmental policies can foster innovation and competitiveness. The rural coal-coupled biomass power generation model introduced in this work represents the convergence of green economy principles and financial systems, serving as a valuable guide for decision-making in decisions aimed at sustainable consumption and production. Moreover, this research underscores the importance of resilient and adaptable energy systems, proposing a pathway for evaluating emission trading markets and promoting sustainable economic recovery strategies that align with environmental sustainability goals.

Keywords: sustainable energy economy; artificial intelligence; energy transition efficiency; energy planning; biomass-coupled power generation

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1. Introduction

With the ascendancy of sustainable energy, clean sources such as solar, wind, and hydropower are progressively emerging as primary alternatives to traditional energy sources. However, the instability and intermittency of these renewable energy sources pose challenges to the reliability and stability of energy systems [1]. Simultaneously, there is an increasing global call for promoting energy transition. To enhance the efficiency of renewable energy utilization and mitigate the environmental burden of energy production and consumption, artificial intelligence (AI) technology has emerged [2–4]. The application of AI in the energy field can be broadly categorized into several aspects. First, AI can optimize energy production plans and enhance energy production efficiency by employing advanced data analysis and prediction algorithms in the energy production process. Second, AI can play a pivotal role in energy storage and distribution, facilitating efficient energy utilization through intelligent management. Additionally, AI can provide innovative solutions on the energy consumption side, reduce energy waste through technologies such as smart homes and intelligent transportation, and promote the intelligent transformation of energy consumption.

The world is facing serious environmental challenges, of which climate change is one of the most prominent. According to the United Nations Environment Programme, global average temperatures have risen by about 1.1 degrees Celsius since industrialization, leading to an increase in the frequency and intensity of extreme weather events, with serious impacts on ecosystems and human societies [5]. At the same time, there is an imbalance between energy supply and demand around the world, which has led to over-reliance on traditional energy resources, exacerbating the negative impact on the environment. According to the International Energy Agency, global energy demand is continuing to grow and is expected to increase by 25% by 2030, with the majority of energy demand relying on fossil fuels [6]. This unbalanced energy mix has led to a continuous increase in carbon emissions, exacerbating the problem of climate change and environmental pollution.

In response to these environmental challenges, the application of AI in energy planning has great potential and advantages, especially in the field of rural energy planning. In China, for example, energy supply in rural areas faces many challenges, including unstable supply and low energy efficiency. AI technology can optimize the energy supply structure and improve energy utilization efficiency through the analysis and prediction of big data, thus reducing carbon emissions and environmental pollution. Miskat et al. [7] proposed that by using AI technology to optimize energy planning, intelligent management of energy consumption could be realized in rural areas and energy costs could be saved. Moreover, energy utilization efficiency could be improved, and sustainable development of the local economy could be promoted [7]. AI technology can also predict and respond to variations in energy demand, adjust the energy supply structure in advance, and ensure the stability and sustainability of the energy supply. Therefore, the widespread application of AI technology in rural energy planning is of great significance for achieving carbon neutrality and promoting the green transition.

The widespread application of renewable energy represents an effective strategy for alleviating energy crises and reducing environmental impacts [8–10]. However, the planning and operation of energy systems face unprecedented complexity due to the uncertainty of renewable energy. This circumstance mandates the continual exploration of innovative solutions aimed at optimizing both the structure and operation of energy systems, thereby augmenting their adaptability to a wide range of energy sources. Conventional energy systems typically revolve around the production and utilization of a singular energy source, whereas multi-energy coupling systems integrate diverse forms of energy, including solar, wind, and biomass, fostering a complementary and synergistic energy usage. This system integration elevates energy efficiency and bolsters the system's resilience to risk, ultimately rendering the energy system more flexible and sustainable. As an emerging trend, BIOMASS-coal coupling technology injects new vitality into energy transition [11,12]. Combining biomass energy with traditional coal systems can mitigate the adverse environmental effects of fossil fuel use and potentially improve the efficiency of coal-fire power generation. With the incorporation of AI technology, biomass-coal coupling systems can intelligently regulate the blend ratio of biomass and coal, thereby realizing a more flexible and sustainable power generation mode [13,14].

This study aims to conduct an in-depth investigation into the simulation of energy system planning integrated with artificial intelligence (AI) and the optimization of multi-energy coupling, with a specific emphasis on the application of biomass-coal coupling technology. Through systematic research, the objective is to present innovative solutions aimed at enhancing the efficient operation of energy systems, reducing environmental impacts, and providing significant scientific foundations for building a sustainable energy economy. By exploring the application of AI in the energy sector, this study strives to identify intelligent, cost-effective, and environmentally responsible solutions for the upcoming energy transition.

This work not only provides theoretical support and practical guidance for rural energy planning and energy transition, but also offers new thinking and ways for achieving sustainable development goals and environmental governance. By exploring the role of AI-enhanced multi-energy optimization in rural energy planning, this work affords a new perspective and method for achieving carbon neutrality and enhancing environmental governance. In addition, an innovative planning scheme has been proposed that takes into account the geographical and economic differences in rural areas and provides specific solutions for the optimization of energy systems in different areas, helping to promote the development of a sustainable energy economy. A comparative analysis of energy demand, conservation, efficiency, and economic indicators across different counties shows the potential to contribute low-carbon practices to agriculture, urban development, and industry domains. This study provides valuable insights into the dynamics of government–business interactions in environmental governance, thereby corroborating Porter's hypothesis, which posits that stringent environmental regulations have the potential to stimulate innovation and enhance competitiveness. A coupled coal-biomass power generation model in rural areas demonstrates the integration of green economy principles with the financial system, offering a valuable reference for planning decisions aimed at sustainable consumption and production. The importance of building resilient energy systems is emphasized, and a pathway is provided for evaluating emissions trading markets and promoting sustainable economic recovery strategies aligned with environmental sustainability goals. Through empirical research and model construction, this work provides a scientific basis for rural energy system planning, especially in the development characteristics and energy demand of different regions in eastern, central, and western China. These results are closely related to current policies and give an important reference for future policy formulation, especially in promoting the development of rural energy systems in a clean, low-carbon, and efficient direction. This work explores the relationship between air pollution control and housing price stability and furnishes a new perspective for the development of comprehensive environmental management strategies. The potential of solar photovoltaic and wind power generation projects is evaluated, and strategies and suggestions are provided for promoting green transformation and improving energy efficiency in western regions such as Z County.

2. Literature Review

In the pursuit of energy transition efficiency, AI technology plays a pivotal role due to its ability to process big data and optimize complex systems intelligently. Through big data analysis, potential energy wastage and bottlenecks can be identified, providing valuable data support for the optimization of energy production and consumption. Simultaneously, AI's deep learning algorithms are capable of recognizing patterns within vast datasets, thereby facilitating the intelligent control and management of energy systems.

Liu et al. [15] emphasized the utility of AI technology in predicting and optimizing renewable energy sources (particularly wind and solar energy) in the context of energy production. Through the forecasting of energy output and adapting production plans accordingly, AI has the potential to enhance energy production efficiency by continuously monitoring weather conditions and the status of energy production equipment. Tutak et al. [16] highlighted that intelligent power system management was a significant application area of AI technology in energy production. AI could optimize power system operations by monitoring grid loads and equipment conditions in real-time to improve the power supply's stability and reliability.

Countries and regions globally are formulating and updating energy plans to balance economic growth and environmentally sustainable development. Nishant et al. [17] suggested that combining biomass energy with traditional coal systems could result in cleaner and more efficient energy utilization. The widespread adoption of this technology can become a crucial means of reducing carbon emissions and improving energy efficiency in the future. The application of AI technology in biomass-coal coupling systems also has significant potential, allowing for intelligent control of biomass and coal to enhance overall system performance. In energy storage and distribution, AI can be applied to battery technology, smart connected charging stations, and other areas to achieve efficient storage and distribution of electric power. Vanegas Cantarero [18] proposed that AI could extend battery life and enhance energy storage efficiency through intelligent management of battery charging and discharging processes. In power distribution, AI can enhance system flexibility and adaptability by intelligently adjusting power distribution schemes based on real-time monitoring of grid loads and predicting electricity demand.

Wang et al. [19] focused on the risk prediction and credibility detection of network public opinion (NPO) and used blockchain technology for optimization. They employed smart contracts to establish an NPO risk management system and tracked public opinion using risk correlation tree technology. Their research findings revealed that, under blockchain technology, the three experimental schemes designed could accurately predict the risk of NPO and assess its credibility, aligning with the objectives of this study. Deng et al. [20] evaluated the economic resilience of coal resource-based cities under low-carbon economic growth conditions. They enhanced the vitality of the economic market in resource-based cities by promoting public participation mechanisms through increased government policy intervention. The findings revealed that from 2011 to 2021, the economic resilience levels of traditional cities and coal resource-based cities fluctuated and increased. In 2011, the economic resilience indices of traditional cities and coal resource-based cities were 0.11 and 0.22, respectively. By 2021, the economic resilience assessment stabilities of the two cities were 0.527 and 0.562, respectively. Li et al. [21] discovered that pilot policies in low-carbon cities generally inhibited enterprise activities, but the level of green innovation could alleviate this inhibitory effect. Through heterogeneity analysis, they found that these pilot policies had a more pronounced inhibitory effect on enterprise activities in central and western regions, resource-based cities, and non-central cities. Furthermore, the pilot policy hindered enterprise activities in high-carbon industries while promoting those in emerging industries, resulting in industrial structural transformations and upgrades. Li et al. [22] implemented a corresponding clean energy development path and ecological environment sustainable development analysis model based on big data technology. They evaluated the feasibility and potential benefits of promoting and applying clean energy in mining projects. The results indicated that under varying GDP growth rates, the new and cumulative installed capacity of global wind energy exhibited an increasing trend. It is anticipated that new wind capacity will increase significantly by 2030 with economic growth. The reduction in CO_2 emissions will continue to increase through 2060. Li et al. [23] studied the impact of climate change on corporate environmental, social, and governance (ESG) performance. Based on the empirical results, they found that climate change significantly inhibited corporate ESG performance. Meanwhile, they discovered that continued elimination of internal and external resource misallocation could help mitigate the adverse effects of climate change on ESG performance. In addition, compared to enterprises in non-resource-based cities, climate change significantly improved the corporate ESG performance of the resource-based city, indicating that the adaptive behavior caused by climate change partially broke the resource curse phenomenon. Furthermore, mature and large enterprises could better mitigate negative impacts, and external pressures from the public environment and analyst attention can motivate enterprises to improve their ESG performance. Wang et al. [24] established various time frames by implementing an iterative process of data platform management and evaluated the impact of three models using indicators such as public participation and government satisfaction. The research results illustrated that the combination of data platform management and multi-model methods effectively enhanced the anti-corruption and prevention capabilities of grassroots governments, offering inspiration for establishing transparent and efficient grassroots governance. Li et al. [25] contended that intellectual property pledge financing hindered corporate innovation, particularly in terms of innovation quality. However, this model can be overturned by elevating the threshold for innovation conditions. The rationale behind this is that stringent innovation criteria may result in enterprises having weaker innovation foundations, which are less susceptible to fluctuations in funds obtained through intellectual property pledge financing. Liu et al. [26] emphasize the significant potential of integrating machine learning technology into various systems, including energy systems, to enhance efficiency and sustainability. Specifically, in the realm of rural energy planning, AI-driven multi-energy optimization methods can identify the optimal energy mix, forecast energy supply and demand patterns, and facilitate real-time adjustments. This ensures efficient and sustainable energy utilization, thereby significantly promoting green transformation. Not only does this contribute to reducing carbon emissions and mitigating environmental degradation, but it also effectively enhances the resilience and reliability of rural energy systems.

In typical rural settings, there exists a dearth of research pertaining to the development of energy system models, planning configurations, and operational optimization strategies. This deficit stems from the unique network characteristics, intricate multi-energy coupling structures, and the influence of specific scenarios on rural energy systems. The present work aims to address this gap by delving deeper into the energy coupling processes within multi-energy coupling scenarios in rural energy systems. It establishes a multi-level energy hub model, thereby laying a solid theoretical foundation for operational optimization.

3. Research Methodology

3.1. Energy System Supply Patterns in Rural Areas of China

The evolution of the supply model in modern rural energy systems focuses on improving the accessibility of electricity, heat, and clean energy while emphasizing sustainability and intelligent management. The primary concern in this model is to provide reliable and stable power. Figure 1 illustrates the special supply model. Traditional grid power supply is progressively integrated with distributed energy systems, encompassing solar photovoltaic and wind power generation [27–29]. Distributed energy systems mitigate reliance on centralized electricity grids and bolster the resilience of electricity supply. Renewable energy sources such as solar and wind present novel avenues for electricity supply and serve as clean alternatives for heat and other forms of energy. Installing solar photovoltaic panels and utilizing wind turbines make rural energy systems greener and lower in carbon footprint, thereby diminishing dependency on conventional energy sources and fostering sustainable development.

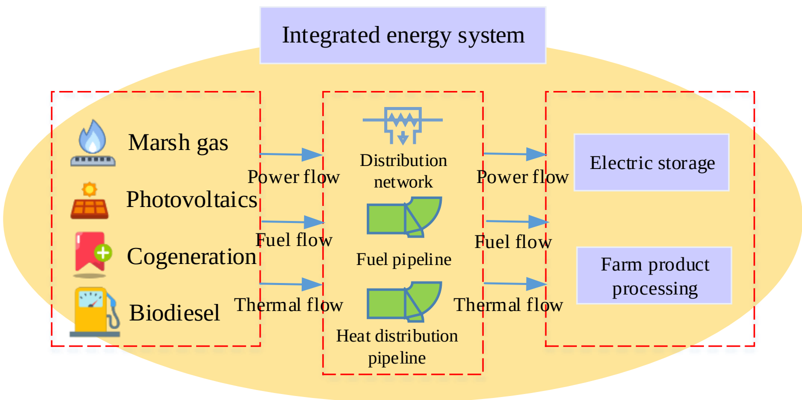

Figure 1. Modern supply pattern of energy systems in rural areas.

Rural energy development in China can be categorized into three types based on geographical location: eastern, central, and western regions, each exhibiting distinct development scenarios as outlined in Table 1. The eastern region, situated along the coast with a low elevation, experiences short winters, high temperatures throughout the year, and abundant rainfall. Some coastal areas benefit from good year-round sunlight and distinct monsoons, making the construction of complementary wind and solar energy systems highly efficient. These areas are at the forefront of national development. Leveraging their exceptional geographical and climatic advantages, they have established a robust industrial and agricultural base, playing a pivotal role in the national economy. Primarily relying on industrial development to drive their economies, these regions have witnessed significant progress in agriculture, forestry, animal husbandry, and fisheries, coupled with abundant biomass energy resources. These regions have relatively well-established power grids, enabling the active promotion of renewable energy transformation and encouraging the use of clean energy such as natural gas [30].

Table 1. Scenarios of differentiated energy development in different areas.

Classification Criteria	Dimension	Development Characteristics	Energy-Resource Structure
Economic situation	Developed type	Agriculture, industry, and other sectors are developing rapidly, resulting in high energy consumption.	The energy is diversified, with electricity and natural gas as the primary sources.
	Underdeveloped type	The energy infrastructure is relatively lagging behind.	They possess natural renewable energy sources with minimal energy loss.
Geographical zone	Eastern region	Economic development is fast, and there is relatively low demand for heating.	Solar energy resources are moderate, with a focus on developing clean energy.
	Central region	The power grid is relatively well-developed, with some areas having heating needs.	Abundant straw resources drive the centralized utilization of biomass.
	Western region	The northwest region experiences cold winters, while the southwest region has a mild climate.	Solar, wind, and other renewable energy sources are clean and abundant.

The central region has a moderate climate, with most areas being plains surrounded by plateaus and hills. Rural electrification infrastructure is relatively well-developed, with electricity being the main energy source [31–33]. With longer average sunlight hours, photovoltaic units can serve as distributed power sources for local users. These areas should continue to promote the construction of energy systems centered around electricity while upgrading and improving weak power grids.

Western rural areas can be divided into southwest and northwest types. The southwest region has a mild climate with hot and rainy summers and is rich in hydropower and solar resources. It is suitable for developing hydropower projects and distributed photovoltaic power systems. The northwest region experiences cold winters, relatively late development, limited transportation conditions, and an overall lower development level. Despite abundant renewable energy resources, there is potential to develop energy systems based mainly on renewable energy sources. In summary, some areas in the western region have abundant renewable energy resources but struggle to efficiently utilize local renewable resources due to economic constraints. These areas need to focus on improving power infrastructure while addressing the conversion issues of local renewable energy resources. Scenarios of differentiated energy development in various areas are exhibited in Table 1.

3.2. Energy System Planning Models with the Coupling of Different Energy Sources

Biomass, such as straw and sawdust, can be obtained through agricultural and forestry resources, while coal is a traditional and reliable energy source. Coupling these two types of energy can effectively utilize renewable resources while maintaining the energy system's stability. The advantage of the bio coal combined unit lies in its stability and reliability. Compared to a single energy source, the combination of biomass and coal can balance energy supply and reduce dependence on specific energy sources. This is particularly important for rural areas, especially considering the impact of climate and the seasons on energy demand. However, when exploring the combination of bio coal and other sustainable energy models, it is necessary to recognize that there may be differences in environmental impacts across various regions. Especially in the western regions of China, the combination of bio coal and pure coal models may have varying degrees of impact on the local environment. For example, in the northwest region, due to the harsh climate conditions and geographical limitations, the pure coal model may lead to more serious air pollution problems and may have adverse effects on local water resources and soil. In the southwest region, a coal combination may be more suitable, but its impact on the local ecosystem also needs to be carefully evaluated. Therefore, regarding energy system planning and environmental governance, it is required to comprehensively consider the characteristics and environmental impacts of diverse regions and take corresponding measures to mitigate potential negative impacts. Future research can further explore the environmental effects of different energy models in the western region and propose targeted environmental management suggestions to promote sustainable energy development and environmental protection.

When optimizing capacity configuration, it is essential to consider the characteristics of energy demand in areas. By establishing demand prediction models based on historical data and meteorological conditions, the seasonal variations in electricity and heat demand can be more accurately estimated, providing a practical basis for subsequent optimization. The construction of a capacity optimization configuration model is a crucial step [34–36]. System efficiency can be maximized through mathematical planning methods. It can ensure that the capacity of biomass-coal coupling units meets demand while maintaining the economic and environmental sustainability of the system. This process requires a comprehensive consideration of the reliability of the biomass supply chain, the upgrading of coal technology, and the scheduling strategy of the system.

The overall planning of energy systems, as opposed to the independent operation of individual energy systems, is effective in dealing with various energy complementarity and coupling relationships [37]. This integrated planning can overcome the limitations of separate planning for heterogeneous energy sources, significantly improving the energy utilization efficiency within the region and enhancing the overall efficiency of the energy system. In overall planning, addressing the coupling relationship of various energies within the energy system is one of the key issues. The energy hub is abstracted to an input-output port model that describes the energy conversion and storage relationships between sources, networks, loads, and storage in the energy system [38–40]. The black box model in Figure 2 is employed, where the black box part is considered as the multi-energy flow system to be analyzed and characterized through the energy hub. In this model, vector P represents energy input and vector L represents energy output. This modeling approach is highly abstract and can transform discrete sub-optimization problems in the energy system into a more comprehensive overall optimization problem.

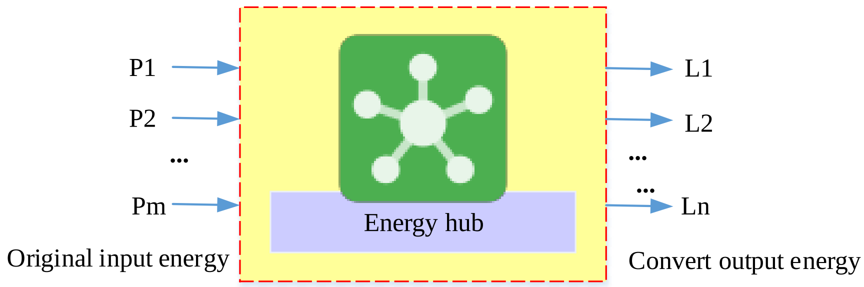

Figure 2. Black box model of energy system ports.

In modern science and technology, grey system theory is a vital quantitative analysis method. Its main feature is to analyze and forecast in the case of insufficient data and high uncertainty. The grey prediction model is one of the applications of grey system theory, which is mainly employed to deal with the prediction problem in the case of a small amount of data and lack of regularity. Different from the traditional mathematical model, the grey prediction model does not need to make strict mathematical assumptions about the data but makes flexible analysis and prediction according to the characteristics and regularity of the data. This work utilizes a grey prediction model to forecast electricity consumption in rural areas to help understand the changing trend of energy demand in various areas. The grey model is characterized by its relatively simple structure, low sample quantity requirement, and suitability for short- to medium-term predictions. Given the specificity of load forecasting, it is considered particularly suitable for load forecasting, where historical data are limited and the data structure is relatively uniform. According to Wu et al. [41]'s water quality prediction method combined with an autoregressive integrated moving average and clustering model and Yang and Ran [42]'s study on China's carbon emission prediction and its driving factors [41], the prediction accuracy of the grey model is higher when the historical data is small. However, when faced with long time series data, the fitting effect may decrease because the model may not be able to fully capture the complex long-term trends and fluctuations between the data.

To further enhance the prediction model's accuracy, this work incorporates some optimization measures into the grey model. First, a sliding average method is employed to smooth the data fluctuations for the first-fit data. Second, a quadratic fitting method is introduced to make the predicted values closer to the actual situation, enhancing the model's fitting capability. Lastly, to account for the influence of external factors, a policy fluctuation term is introduced to consider potential interfering factors more comprehensively.

n original data points are input to form the original data sequence, represented as:

$$X^{(0)} = \left(x^{(0)}(1)x^{(0)}(2)\ \ldots x^{(0)}(n)\right)^T \tag{1}$$

First-order summation is performed on Equation (1), and it can be obtained that:

$$x^{(1)}(n) = \sum_{i=1}^{n} x^{(0)}(i) \tag{2}$$

The obtained new sequence can be represented as:

$$X^{(1)} = \left(x^{(1)}(1)\ \ x^{(1)}(2)\ \ldots x^{(1)}(n)\right)^T \tag{3}$$

The solution to the first-order differential equation is in exponential form, satisfying the following equation:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \tag{4}$$

a and u are parameters of the whitening differential equation.

a and u can be solved through the least squares method in matrix form.

$$\begin{bmatrix} a \\ u \end{bmatrix} = \left(B^T B\right)^{-1} B^T YN \tag{5}$$

Due to the complexity of real-world data conditions, using a large amount of data directly may result in significant errors. To mitigate the impact of outliers, it is recommended to apply a moving average to the original sequence before constructing the exponential growth sequence, as shown in Equation (6):

$$x(n) = \frac{x(n-1) + 2x(n) + x(n+1)}{4} \tag{6}$$

$x(n)$ represents the original data values.

In order to enhance prediction accuracy, a second-order fitting is performed on the forecast data of the grey model. The exponential growth model for the first fit is:

$$x(t+1) = \left[x^{(0)}(1) - \frac{u}{a}\right]e^{-at} + \frac{u}{a} \tag{7}$$

The second-order fitting involves solving for the function of Equation (8) as the objective function:

$$x\prime(t+1) = M \cdot e^{-at} + N \tag{8}$$

$$\begin{bmatrix} M \\ N \end{bmatrix} = \left(G^T G\right)^{-1} G^T X\prime \tag{9}$$

The policy volatility term is expressed as:

$$e(t) = x(t) \cdot A \cdot F(t) \tag{10}$$

$x(t)$ is the exponential function obtained after fitting, A represents the volatility amplitude, and $F(t)$ refers to the policy affiliation function.

After obtaining the results of exponential growth through second-order fitting, the policy volatility term is incorporated, and its focus is on the subsequent prediction section. Coupled biomass and coal units play a significant role in energy planning, providing a feasible option to improve energy efficiency and reduce environmental impact [43,44]. The development of a capacity planning model aims to optimize the configuration of these units to meet the growing energy demands in areas. The first step involves preprocessing energy load data, considering the impact of policy factors on the load. The model is then used to obtain the total capacity of biomass gasification furnaces [45–47]. In this step, the model considers the coupling of coal and biomass to meet the energy needs of rural areas. Figure 3 depicts the specific process of optimizing the capacity of biomass-coupled coal units.

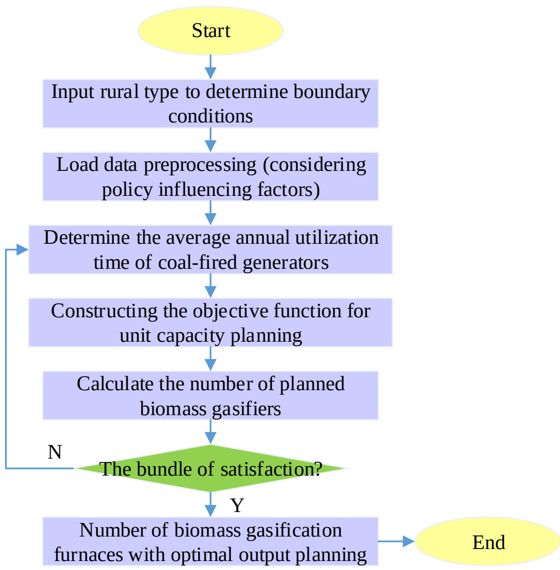

Figure 3. Capacity optimization of biomass-coal coupling units.

3.3. Optimization of Energy Systems Based on AI-Driven Planning and Operation

In the planning scenario of energy systems, it is essential to comprehensively consider the focal points of different types of areas in the energy transition path. Due to the background of diversified energy development, diverse areas show significant variations in their requirements for various indicators. In this in-depth exploration of the differentiated development scenarios of energy systems, an innovative energy system planning scheme is proposed (Figure 4). In this scheme, based on two dimensions, namely the geographical location and economic development status of areas, corresponding indicator weight factors are assigned for different types of areas. "Indicator weight factor" refers to the weight coefficients assigned to various indicators in energy system planning for different rural areas based on their geographical location and economic development status. These indicators may involve energy consumption, environmental impact, economic benefits, and more. By assigning different weights to different indicators, they can more accurately reflect the energy demand and characteristics of various areas, thus achieving more effective energy planning. This precise allocation helps to capture the unique needs of each area more accurately, enabling more flexible and effective energy planning.

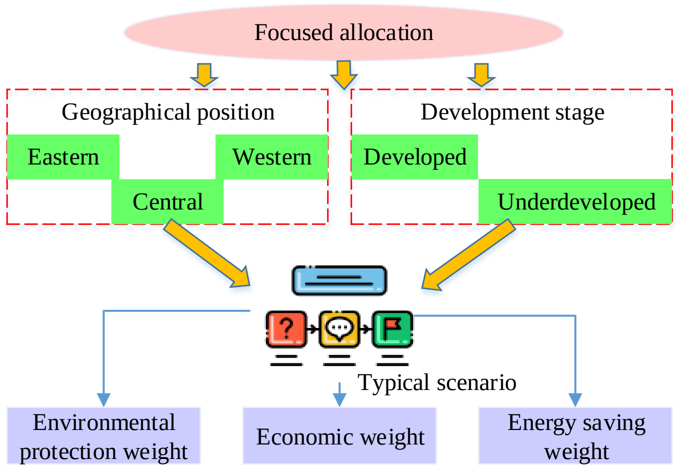

Figure 4. Process of allocating indicator weight factors for different types.

Machine learning also plays a crucial role in optimizing energy production and distribution. Machine learning systems can identify potential performance issues by continuously monitoring and analyzing real-time operational data from energy production equipment, improving equipment efficiency and effectiveness. Genetic programming (GP), as an advanced evolutionary algorithm, utilizes natural selection principles to optimize problem solutions. Niazkar et al. [48] used multi-gene genetic programming (MGGP) and artificial neural network (ANN) to downscale three general circulation models. Among them, the GP model demonstrated strong capabilities in dealing with large amounts of data and complex correlations between variables, making it particularly suitable in the energy system configuration and optimization fields [49]. GP is an AI evolutionary algorithm that simulates the natural evolution process to gradually evolve programs or structures adapted to specific problems. GP provides an innovative approach to optimizing the structure and configuration of energy systems. In the GP algorithm, individuals are typically represented by tree structures where each node of the tree represents an operator or variable. The tree can be expressed through a string of symbols (genetic encoding). The encoding method is as follows:

$$I = (o, T_1, T_2) \tag{11}$$

I represents an individual, o means the operator at the root node of the tree, T_1 and T_2 are the left and right subtrees of the tree, respectively.

The fitness function evaluates the performance of an individual and is typically defined based on the objectives and constraints of the problem. It can be expressed as:

$$F(I) = \frac{1}{1 + error(I)} \tag{12}$$

$F(I)$ refers to the fitness of the individual I, and $error(I)$ represents the error or inadaptability of the individual in the solution space.

GP autonomously generates programs that fit specific objectives by simulating the biological evolution process. In energy systems, GP can be employed to optimize the structure and configuration of energy systems, enhancing the system's overall efficiency.

3.4. Experimental Data

The data utilized in this work predominantly emanate from rural energy systems across various regions of China, with three representative locales being X County in Yantai

City, situated in eastern China; Y County in Luoyang City, located in central China; and Z County in Lanzhou City, situated in western China. These regions epitomize China's rural energy development landscape, encapsulating the nuances of rural energy systems across distinct geographical and economic spectra. The selection of these regions is predicated on their capacity to exemplify the diversity and intricacies of energy development in China, thus facilitating a comprehensive appraisal of the challenges and opportunities inherent in rural energy planning and management. The dataset pertaining to these regions exhibits a high degree of representativeness, thereby efficaciously underpinning the empirical analysis of energy system planning and optimization. Aligned with the research inquiry's pertinence, this work aims to investigate avenues for advancing rural energy planning and fostering sustainable energy economy development through AI-facilitated multi-energy optimization. Consequently, the chosen data is intricately intertwined with the research question, enabling a nuanced examination of energy demand, supply structure, economic attributes, and environmental ramifications across diverse regions. By scrutinizing these data, a more profound comprehension of the prevailing state and extant challenges within the energy system can be attained, thereby furnishing a scientific framework for the formulation of efficacious energy planning strategies and policies. As such, it is posited that the selected data holds significant relevance to the discourse surrounding the research questions and augments the credibility and persuasiveness of the research findings.

4. Experimental Design and Performance Evaluation

4.1. Scenario Case Analysis Experiment

Based on project data support, this study selected three regions in China (located in the eastern, central, and western parts) for a detailed case analysis due to their differentiated development patterns. These regions specifically include X County in Yantai City (east), Y County in Luoyang City (central), and Z County in Lanzhou City (west). These areas are chosen as representative validation scenarios, enabling an in-depth examination of various facets of energy development and establishing a substantial case foundation. Since only X County and Y County are suitable for combining coal and biomass in power generation, we have compiled the relevant optimization configuration parameters for this coupling (Table 2). Given that the selected simulation objects cover economically developed stages in X and Y counties, it can be understood that these areas, influenced by national policies, belong to the new agricultural development stage and have made significant progress, making them representative of the new model. This development status underscores the significant impact of adjustments in energy transition policies on their progress.

Table 2. Related optimization configuration parameters for coal-biomass coupling power generation in X County and Y County.

Basic Parameters		Numerical Values
Coal-fired unit capacity (MW)	X County	330
	Y County	660
Biomass supply quantity (t/month)	X County	3500
	Y County	5000
Raw material recycling price (yuan/t)	Standard coal	530
	Biomass	300
Pollutant gas emission coefficient (kg/(kW·h))	CO_2	52.160
	NO_X	2.398
	SO_2	5.397

4.2. Prediction Results of Grid Transformation Project

In the modeling process of grey forecasting, the accuracy of the forecast results do not necessarily increase with the increase in historical data. For optimal results, this study opts to utilize eight datasets for forecasting, specifically focusing on electricity consumption from 2014 to 2022. Figures 5 and 6 depict the electricity consumption prediction data for X and Y counties. Observations indicate that X County's three primary industries are flourishing, with agriculture forming a smaller part of its economic structure. The growth rate in such areas remains at a high level in multiple periods but fails to consistently sustain the same level of growth. Y County's development is primarily dominated by agriculture, and compared to areas like X County, the effects of transformation policies are more pronounced. The electricity consumption in X County is significantly higher than that in Y County. The decision for Y County to expand its biomass coal coupling scale or explore alternative energy development paths hinges on several considerations. If the growth forecast of electricity consumption in Y County shows a remarkable increase in energy demand in the future, expanding the scale of biomass coal coupling may be a feasible option. Expanding the scale of coupling requires consideration of economic costs, return on investment, and potential environmental impacts. If the cost-effectiveness of scaling up is comparatively high and meets environmental protection requirements, then this may be a worthwhile option to consider. The availability and sustainability of biomass resources are key factors in determining whether to expand the scale of biomass coal coupling. If Y County has abundant biomass resources and can ensure long-term supply, this supports the decision to expand the coupling scale. The energy policies, environmental regulations, and support for renewable energy by national and local governments also affect the decision-making of Y County. If some more advanced technologies or methods can improve the efficiency or reduce the costs of biomass coal coupling, it may also prompt Y County to consider expanding its scale. In addition to expanding the scale of biomass coal coupling, Y County can also explore other energy development methods such as increasing the use of renewable energy (solar and wind energy) to achieve diversified energy supply and risk diversification. When considering expanding the scale of biomass coal coupling or adopting other energy development methods, it is also necessary to evaluate the potential impact of these measures on the economy and society, encompassing their influence on local employment, industrial development, and the quality of life of residents. In conclusion, Y County's decision to expand biomass coal coupling or pursue alternative energy strategies demands a thorough analysis and evaluation. This involves a comprehensive consideration of factors such as energy demand forecasting, resource availability, economic benefits, environmental impact, policy support, and technological innovation.

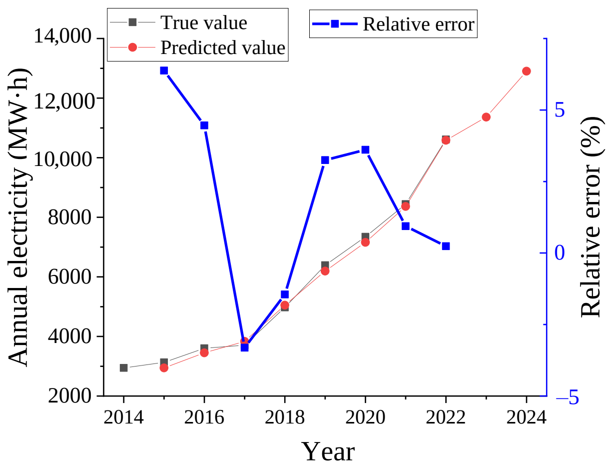

Figure 5. Electricity consumption prediction for X County.

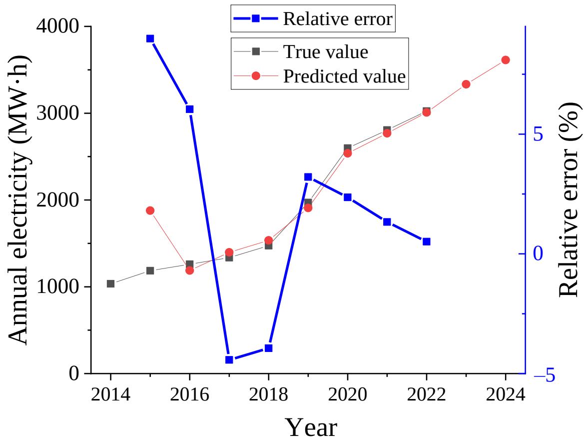

Figure 6. Electricity consumption prediction for Y County.

There are differences in the total annual typical daily load of X, Y, and Z counties, as well as variations in resource distribution. Two-tier planning refers to a strategy that takes both geographical location and economic development into account in energy system planning. In this work, two-tier planning is used to comprehensively consider the energy needs and sustainable development goals of diverse regions and formulate corresponding energy planning according to each region's characteristics. To effectively evaluate the planning effectiveness of dual-layer planning and analyze the impact of different weight indicators in each typical scenario, the results obtained from the planning model are normalized. Figure 7 displays the economic analysis results. X County has a high demand for a typical daily load, mainly to meet local industry and agriculture production, with energy-saving as the primary focus in its energy transition path. In the planning of energy transition pathways, the different focus of different types of rural areas leads to the different weights of demand indicators. The optimal allocation results of biomass-coal coupled power generation capacity are based on these weighting factors so that the optimized power generation capacity allocation scheme can reflect the unique energy needs of each area more accurately. The proportion of energy consumption costs in X County is relatively lower compared to Y County and Z County, at 3.28%. This indicates that the proposed optimization model successfully focuses on the region's energy-saving focus in the energy transition path. The planning in Z County emphasizes economic indicators in the model. As a result, the initial investment costs after planning in Z County are reduced by 8.55% and 10.26%, respectively, compared to X and Y counties. Y County has a large amount of renewable energy internally, resulting in a higher environmental weight compared to X and Z counties.

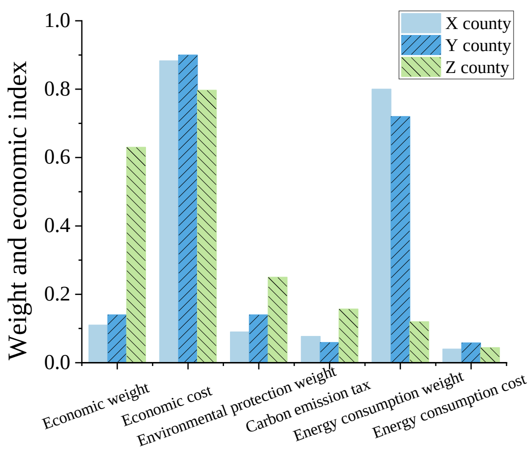

Figure 7. Economic analysis results after target weighting normalization.

In this work, X, Y, and Z counties are taken as research cases, and there are obvious differences in their positioning and main influencing factors in sustainable energy planning. A breakdown of each county follows:

1. X County:

Principal Influencing Factors: the level of industrial and agricultural development and energy consumption efficiency constitute the primary determinants. X County exhibits a relatively advanced industrial and agricultural landscape, rendering energy consumption efficiency a paramount consideration. Given the substantial contributions of industrial and agricultural sectors to energy consumption, enhancing energy utilization efficiency assumes critical importance in mitigating carbon emissions and fostering sustainable development. Accordingly, X County may prioritize the adoption of energy-saving and emission-reduction technologies to enhance energy efficiency across industrial and agricultural domains. Simultaneously, the gradual integration of renewable energy sources to supplant conventional energy sources facilitates the transformation and modernization of the energy structure. Environmental Impact Considerations: owing to the mature development of industry and agriculture, X County exerts a notable environmental footprint. Consequently, imperative environmental conservation measures, such as curbing energy consumption, reducing carbon emissions, and ameliorating air quality emerge as pivotal facets guiding future developmental trajectories.

2. Y County:

Principal Influencing Factors: agricultural dependence and utilization of renewable energy. The economic structure of Y County is mainly based on agriculture, so more attention is paid to the utilization of renewable energy. The biomass resources generated during agricultural production can serve as a critical source of renewable energy. Hence, in energy planning, Y County attaches greater importance to the development and utilization of renewable energy. Y County may be more inclined to develop renewable energy projects such as agricultural waste utilization and biomass energy to meet the energy needs of agricultural production and residents and achieve sustainable development of rural energy. The industrial structure of Y County is mainly based on agriculture, and compared to industrialized areas, its impact on the environment is relatively small. However, attention still needs to focus on potential environmental issues that may arise during agricultural production processes, such as pesticide residues and land degradation.

3. Z County:

Principal Influencing Factors: economic development level and environmental protection demand. Z County is located in the western region of China, with a comparatively low level of economic development. Thus, in energy planning, more emphasis is placed on balancing economic development and environmental protection. With the increasing awareness of environmental protection, the demand for environmental protection is gradually increasing, becoming a vital factor affecting energy planning. Z County may take measures such as developing clean energy and improving energy utilization efficiency to achieve sustainable economic growth while protecting local environmental resources. Due to the relatively low level of economic development, the environmental protection needs in Z County are more urgent. Consequently, in energy planning, it is necessary to pay attention to environmental protection measures such as reducing pollution emissions and improving resource utilization efficiency to achieve a win-win situation between economic development and environmental protection.

4.3. Explanation of Model Results and Policy Relevance

The capacity planning model proposed here is closely related to current policies, and its output is in line with the local policy background, furnishing critical references for future policy formulation. Taking China's rural energy planning as an example, the current Chinese government has proposed the strategic goals of carbon neutrality and sustainable development. It requires improving energy utilization efficiency, promoting energy structure optimization and upgrading, vigorously developing clean and renewable energy sources, and reducing carbon emissions while achieving energy supply security. The proposed model is based on this background, aiming to realize an intelligent and sustainable energy supply by optimizing the energy supply structure.

Drawing from the model outcomes, prospective energy planning initiatives should center on the following focal points. Firstly, optimizing the energy supply structure and augmenting the utilization of clean and renewable energy resources warrant concerted attention. Tailored energy transition pathways can be delineated for diverse rural settings to propel the energy system toward cleaner, low-carbon, and efficient trajectories. For instance, initiatives can entail bolstering the utilization of clean energy sources like solar and wind energy, alongside fostering the incremental integration of renewable energy within rural energy matrices, contingent upon local climatic prerequisites. Secondly, deliberations should ensue on strategies to expedite the adoption of renewable energy and realize carbon neutrality objectives within prevailing policy frameworks. Governments can incentivize corporate entities and individuals to amplify investments in and utilization of renewable energy through proactive policy interventions, including subsidies, preferential tax regimes, and the establishment of carbon markets, thereby advancing the transition toward carbon neutrality. Finally, fortifying the monitoring and evaluation mechanisms about the efficacy of energy planning implementation and promptly recalibrating policy interventions as warranted assumes paramount importance. By instituting a robust monitoring framework and collating data pertaining to energy utilization and environmental indicators, the efficacy of energy planning implementation can be judiciously appraised. Furthermore, policy adjustments are orchestrated in a timely fashion based on evaluation outcomes to ensure the seamless attainment of energy planning objectives.

In short, future energy planning should strengthen measures regarding policy support, technological innovation, market mechanisms, and monitoring and evaluation. Consequently, it can promote the rural energy system's development in a cleaner, more efficient, and sustainable direction, and make positive contributions to the realization of carbon neutrality and sustainable development goals.

4.4. Strategies to Stabilize Housing Prices for Particle Matter and Air Pollution

This work recognizes the close relationship between air pollution control and stable housing prices and realizes that this relationship is crucial for achieving sustainable development goals. Specifically, it should be noted that housing price policies have a significant impact on residents' housing choices and lifestyles, which in turn directly affect energy consumption and emissions. Therefore, it is believed that exploring the impact of housing price policies on particle matter (PM) emissions and air quality, as well as their correlation with air pollution control, is of great significance for formulating comprehensive environmental governance strategies.

Firstly, the impact of housing price policies on urban planning and land use can be analyzed. High housing prices may lead residents to choose to purchase housing in suburbs or places far from the city center, thereby increasing commuting distance and further increasing car exhaust emissions. Thus, the reasonable regulation of housing price policies can indirectly affect the frequency of car use and reduce PM emissions by influencing residents' choices of living locations. Secondly, housing price policies may also affect residents' investment in energy utilization and environmental protection facilities. In cities with high housing prices, residents may be more inclined to purchase newly built high-end housing, which is often equipped with more efficient energy utilization facilities and environmentally friendly equipment, thereby reducing energy consumption and emissions. Hence, the adjustment of the housing price policy may indirectly affect the energy structure of the city and the construction level of environmental protection facilities, and then affect the air quality. Finally, housing price policies may also affect the economic status and lifestyle of residents, thereby affecting their level of attention to environmental issues. The rise in housing prices may lead residents to pay more attention to conservation and environmental protection, such as choosing to purchase energy-saving appliances and reducing energy waste. These behaviors have a positive effect on reducing PM emissions and improving air quality.

According to the above analysis, it is suggested that future research should further explore the relationship between housing price policy and environmental governance, and put forward targeted policy recommendations. For example, the government can guide residents to choose more environmentally friendly living methods and promote green urban development by adjusting housing price policies. The government can also encourage developers to use more environmentally friendly building materials and facilities in new residential buildings by formulating incentive policies, thus reducing the impact of construction on the environment. These policy measures help achieve the dual goals of air pollution control and stable housing prices and promote the development of cities in a more sustainable direction.

4.5. Potential and Challenges of Solar Photovoltaic and Wind Power Generation Projects

Considering the abundant renewable energy resources in Z County and the entire western region, especially the significant potential in solar and wind energy, the research scope has been expanded and the comprehensive optimization allocation of these resources has been evaluated. Utilizing an analytical framework analogous to the biomass-coal coupling model, we have conducted the planning and design of solar photovoltaic and wind power generation systems in Z County, evaluating their stability, economic viability, and environmental implications within the local context. It is believed that although Z County cannot adopt the biomass coal coupling model, there is still broad space in promoting green transformation and improving energy efficiency in the region.

In Z County, an innovative model for the comprehensive utilization of solar and wind energy is adopted, utilizing geographic information systems (GIS) and multi-objective optimization technology to determine the optimal installation location for solar photovoltaic panels and wind turbines. This model considers terrain, sunshine rate, wind speed, and other factors to ensure the maximization of energy output and cost-benefit optimization. The average annual sunshine hours in Z County reach 2200 h, with an average wind speed of 3.5 m per second, providing good conditions for solar and wind energy. Based on geographical analysis, photovoltaic panels are chosen to be installed in the southern region with open terrain and sufficient sunlight. The expected installation capacity is 150 megawatts. Wind turbines are mainly installed in the northern mountainous areas with high wind speeds, with an expected installation capacity of 100 megawatts. The preliminary results of the comprehensive energy system planning are presented in Table 3.

In Z County, considering the lack of combined utilization of biomass coal, planning experiments are carried out on solar and wind energy resources. For solar and wind power generation projects, the following strategies have been adopted. Firstly, a geographical survey and resource assessment are conducted on these projects. By collecting and analyzing climate data, topography, and other information about Z County, suitable locations for constructing projects are determined. Secondly, the layout and capacity of solar photovoltaic and wind power generation systems are designed. Based on the results of the field survey and resource assessment, the location and number of photovoltaic panels and wind turbines are determined to maximize the use of local solar and wind resources. Finally, an operation and maintenance plan is developed. Considering the seasonality and uncertainty of solar and wind energy, an operation and maintenance plan has been developed to ensure the stable operation and effective utilization of solar photovoltaic and wind power generation systems.

Solar and wind power generation projects can bring many benefits to Z County. Solar photovoltaic and wind power generation systems can provide Z County with a clean, renewable energy supply, decrease dependence on traditional energy sources, and reduce environmental pollution. The construction of these projects can create employment opportunities and promote local economic development. At the same time, project operation and maintenance drive the development of related industrial chains, forming an industrial agglomeration effect. The use of clean energy improves the living environment of residents and enhances their quality of life. In addition, the project construction also promotes local energy security and advances social stability and sustainable development.

Table 3. Preliminary results of comprehensive energy system planning.

Energy System Planning		**Numerical Values**
Estimated annual power generation	Solar photovoltaic	180,000 megawatt hours
	wind power generation	120,000 megawatt hours
Economic analysis	Investment cost	The total investment is about 300 million yuan, with a solar photovoltaic investment of 180 million yuan; Wind power investment: 120 million yuan
	Payback period	8 years
Environmental benefits	Reducing CO_2 emissions	Expected to reduce carbon emissions by approximately 260,000 tons annually
	Other pollutants	Compared to coal-fired power generation, NO_x and SO_2 emissions are reduced by approximately 3000 tons

However, these projects' construction also faces some challenges. Solar photovoltaic and wind power technologies require advanced equipment and technical support, and the construction process may face problems such as supply chain disruptions and equipment failures. These projects require a large amount of capital investment, including equipment procurement, engineering construction, operation, and maintenance expenses, and the investment return period is relatively long. Project management and operation require professionals and experienced teams to carry out. Moreover, facing factors such as weather, seasonal changes, management, and operation are difficult. To sum up, while solar photovoltaic and wind power projects bring clean energy supply to Z County, they also face some challenges which need the joint efforts of government departments, enterprises, and all sectors of society to overcome.

A comparative analysis is carried out and the economic and environmental benefits of different energy utilization schemes are re-evaluated in response to the development potential of Z County in renewable energy. Comparative analysis updates and benefit reassessment are listed in Table 4:

Table 4. Comparative analysis update and benefit reassessment.

Energy Utilization Plan	**Economic Benefits (10,000 Yuan/Year)**	**Environmental Benefits (Emission Reduction/Year)**
Solar photovoltaic	500	1000
Wind power generation	450	900
Biomass coal combined utilization	600	1200

Table 4 shows that although the biomass coal combined utilization scheme has outstanding economic and environmental benefits, considering the lack of biomass resources in Z County, solar photovoltaic and wind power generation are still more feasible energy utilization schemes. Hence, it is recommended that government departments and enterprises focus on promoting the construction of solar photovoltaic and wind power generation projects when formulating energy development plans to achieve a win-win situation of economic and environmental benefits.

5. Conclusions

This work successfully advances the green transition of rural energy planning and sustainable energy economy by proposing an innovative AI-based multi-energy optimization model. Case studies of diverse rural areas in eastern, central, and western China demonstrate the model's effectiveness in improving energy efficiency, reducing environmental impact, and promoting economic development. The application results of the model are closely linked with the national carbon neutrality target and the green total factor productivity assessment, thus providing a scientific basis and practical guidance for energy system planning.

Policymakers are advised to consider the following measures. The energy supply structure is optimized, increasing the utilization of clean and renewable energy; Incentive policies are developed to encourage businesses and individuals to invest in renewable energy; A monitoring system is established, the effectiveness of energy planning implementation is evaluated, and policies are adjusted promptly. In addition, it is necessary to recognize the close relationship between air pollution control and housing price stability. Hence, it is recommended that future research further explore the relationship between housing price policies and environmental governance.

Although this work has achieved certain results, there are limitations, and future research can further explore the application of AI technology in the broader rural energy field and develop more refined models and algorithms. Solar photovoltaic and wind power generation projects show great potential in Z County, but they also face technical and financial challenges. Government departments, enterprises, and all sectors of society must work together to overcome these challenges and promote the green transformation and sustainable development of rural energy systems.

This work strongly believes that the use of AI and multi-energy optimization strategies can effectively promote energy planning and transition in rural areas and make a positive contribution to the achievement of global and Chinese sustainable development goals.

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References

1. Chen, C.; Hu, Y.; Karuppiah, M.; Kumar, P.M. Artificial intelligence on economic evaluation of energy efficiency and renewable energy technologies. *Sustain. Energy Technol. Assess.* **2021**, *47*, 101358. [CrossRef]
2. Abdalla, A.N.; Nazir, M.S.; Tao, H.; Cao, S.; Ji, R.; Jiang, M.; Yao, L. Integration of energy storage system and renewable energy sources based on artificial intelligence: An overview. *J. Energy Storage* **2021**, *40*, 102811. [CrossRef]
3. Ahmad, T.; Madonski, R.; Zhang, D.; Huang, C.; Mujeeb, A. Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm. *Renew. Sustain. Energy Rev.* **2022**, *160*, 112128. [CrossRef]
4. Şerban, A.C.; Lytras, M.D. Artificial intelligence for smart renewable energy sector in Europe—Smart energy infrastructures for next generation smart cities. *IEEE Access* **2020**, *8*, 77364–77377. [CrossRef]

5. Leal Filho, W.; Viera Trevisan, L.; Simon Rampasso, I.; Anholon, R.; Pimenta Dinis, M.A.; Londero Brandli, L.; Sierra, J.; Lange Salvia, A.; Pretorius, R.; Nicolau, M.; et al. When the alarm bells ring: Why the UN sustainable development goals may not be achieved by 2030. *J. Clean. Prod.* **2023**, *407*, 137108. [CrossRef]
6. Zou, C.; Ma, F.; Pan, S.; Zhao, Q.; Fu, G.; Zhang, G.; Yang, Y.; Yu, H.; Liang, Y.; Lin, M.; et al. Global energy transition revolution and the connotation and pathway of the green and intelligent energy system. *Pet. Explor. Dev.* **2023**, *50*, 722–740. [CrossRef]
7. Miskat, M.I.; Sarker, P.; Chowdhury, H.; Chowdhury, T.; Rahman, M.S.; Hossain, N.; Chowdhury, P.; Sait, S.M. Current Scenario of Solar Energy Applications in Bangladesh: Techno-Economic Perspective, Policy Implementation, and Possibility of the Integration of Artificial Intelligence. *Energies* **2023**, *16*, 1494. [CrossRef]
8. Nam, K.; Hwangbo, S.; Yoo, C. A deep learning-based forecasting model for renewable energy scenarios to guide sustainable energy policy: A case study of Korea. *Renew. Sustain. Energy Rev.* **2020**, *122*, 109725. [CrossRef]
9. Yigitcanlar, T.; Mehmood, R.; Corchado, J.M. Green artificial intelligence: Towards an efficient, sustainable and equitable technology for smart cities and futures. *Sustainability* **2021**, *13*, 8952. [CrossRef]
10. Yildizbasi, A. Blockchain and renewable energy: Integration challenges in circular economy era. *Renew. Energy* **2021**, *176*, 183–197. [CrossRef]
11. Agostinelli, S.; Cumo, F.; Guidi, G.; Tomazzoli, C. Cyber-Physical systems improving building energy management: Digital twin and artificial intelligence. *Energies* **2021**, *14*, 2338. [CrossRef]
12. Dogaru, L. The main goals of the fourth industrial revolution. Renewable energy perspectives. *Procedia Manuf.* **2020**, *46*, 397–401. [CrossRef]
13. Al-Othman, A.; Tawalbeh, M.; Martis, R.; Dhou, S.; Orhan, M.; Qasim, M.; Ghani Olabi, A. Artificial intelligence and numerical models in hybrid renewable energy systems with fuel cells: Advances and prospects. *Energy Convers. Manag.* **2022**, *253*, 115154. [CrossRef]
14. Palomares, I.; Martínez-Cámara, E.; Montes, R.; García-Moral, P.; Chiachio, M.; Chiachio, J.; Alonso, S.; Melero, F.J.; Molina, D.; Fernández, B.; et al. A panoramic view and swot analysis of artificial intelligence for achieving the sustainable development goals by 2030: Progress and prospects. *Appl. Intell.* **2021**, *51*, 6497–6527. [CrossRef] [PubMed]
15. Liu, X.; Zhao, T.; Chang, C.-T.; Fu, C.J. China's renewable energy strategy and industrial adjustment policy. *Renew. Energy* **2021**, *170*, 1382–1395. [CrossRef]
16. Tutak, M.; Brodny, J.; Siwiec, D.; Ulewicz, R.; Bindzár, P. Studying the level of sustainable energy development of the European union countries and their similarity based on the economic and demographic potential. *Energies* **2020**, *13*, 6643. [CrossRef]
17. Nishant, R.; Kennedy, M.; Corbett, J. Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *Int. J. Inf. Manag.* **2020**, *53*, 102104. [CrossRef]
18. Vanegas Cantarero, M.M. Of renewable energy, energy democracy, and sustainable development: A roadmap to accelerate the energy transition in developing countries. *Energy Res. Soc. Sci.* **2020**, *70*, 101716. [CrossRef]
19. Wang, Z.; Zhang, S.; Zhao, Y.; Chen, C.; Dong, X. Risk prediction and credibility detection of network public opinion using blockchain technology. *Technol. Forecast. Soc. Change* **2023**, *187*, 122177. [CrossRef]
20. Deng, Y.; Jiang, W.; Wang, Z. Economic resilience assessment and policy interaction of coal resource oriented cities for the low carbon economy based on AI. *Resour. Policy* **2023**, *82*, 103522. [CrossRef]
21. Li, C.; Liang, F.; Liang, Y.; Wang, Z. Low-carbon strategy, entrepreneurial activity, and industrial structure change: Evidence from a quasi-natural experiment. *J. Clean. Prod.* **2023**, *427*, 139183. [CrossRef]
22. Li, D.D.; Guan, X.; Tang, T.T.; Zhao, L.Y.; Tong, W.R.; Wang, Z.Y. The clean energy development path and sustainable development of the ecological environment driven by big data for mining projects. *J. Environ. Manag.* **2023**, *348*, 119426. [CrossRef] [PubMed]
23. Li, C.; Tang, W.; Liang, F.; Wang, Z. The impact of climate change on corporate ESG performance: The role of resource misallocation in enterprises. *J. Clean. Prod.* **2024**, *445*, 141263. [CrossRef]
24. Wang, Z.; Guan, X.; Zeng, Y.; Liang, X.; Dong, S. Utilizing data platform management to implement "5W" analysis framework for preventing and controlling corruption in grassroots government. *Heliyon* **2024**, *10*, e28601. [CrossRef] [PubMed]
25. Li, Y.; Zhang, Y.; Hu, J.; Wang, Z. Insight into the nexus between intellectual property pledge financing and enterprise innovation: A systematic analysis with multidimensional perspectives. *Int. Rev. Econ. Financ.* **2024**, *93*, 700–719. [CrossRef]
26. Liu, T.; Guan, X.; Wang, Z.; Qin, T.; Sun, R.; Wang, Y. Optimizing green supply chain circular economy in smart cities with integrated machine learning technology. *Heliyon* **2024**, *10*, e29825. [CrossRef]
27. Ghadami, N.; Gheibi, M.; Kian, Z.; Faramarz, M.G.; Naghedi, R.; Eftekhari, M.; Fathollahi-Fard, A.M.; Dulebenets, M.A.; Tian, G. Implementation of solar energy in smart cities using an integration of artificial neural network, photovoltaic system and classical Delphi methods. *Sustain. Cities Soc.* **2021**, *74*, 103149. [CrossRef]
28. Østergaard, P.A.; Duic, N.; Noorollahi, Y.; Mikulcic, H.; Kalogirou, S. Sustainable development using renewable energy technology. *Renew. Energy* **2020**, *146*, 2430–2437. [CrossRef]
29. Shahbaz, M.; Wang, J.; Dong, K.; Zhao, J. The impact of digital economy on energy transition across the globe: The mediating role of government governance. *Renew. Sustain. Energy Rev.* **2022**, *166*, 112620. [CrossRef]
30. Yigitcanlar, T.; Desouza, K.C.; Butler, L.; Roozkhosh, F. Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature. *Energies* **2020**, *13*, 1473. [CrossRef]
31. Di Vaio, A.; Palladino, R.; Hassan, R.; Escobar, O. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *J. Bus. Res.* **2020**, *121*, 283–314. [CrossRef]

32. Xiang, X.; Li, Q.; Khan, S.; Khalaf, O.I. Urban water resource management for sustainable environment planning using artificial intelligence techniques. *Environ. Impact Assess. Rev.* **2021**, *86*, 106515. [CrossRef]
33. Xu, X.; Wei, Z.; Ji, Q.; Wang, C.; Gao, G. Global renewable energy development: Influencing factors, trend predictions and countermeasures. *Resour. Policy* **2019**, *63*, 101470. [CrossRef]
34. Awan, A.; Abbasi, K.R.; Rej, S.; Bandyopadhyay, A.; Lv, K. The impact of renewable energy, internet use and foreign direct investment on carbon dioxide emissions: A method of moments quantile analysis. *Renew. Energy* **2022**, *189*, 454–466. [CrossRef]
35. Mhlanga, D. Artificial intelligence in the industry 4.0, and its impact on poverty, innovation, infrastructure development, and the sustainable development goals: Lessons from emerging economies? *Sustainability* **2021**, *13*, 5788. [CrossRef]
36. Zhong, Z.; Peng, B.; Xu, L.; Andrews, A.; Elahi, E. Analysis of regional energy economic efficiency and its influencing factors: A case study of Yangtze river urban agglomeration. *Sustain. Energy Technol. Assess.* **2020**, *41*, 100784. [CrossRef]
37. López González, D.M.; Garcia Rendon, J. Opportunities and challenges of mainstreaming distributed energy resources towards the transition to more efficient and resilient energy markets. *Renew. Sustain. Energy Rev.* **2022**, *157*, 112018. [CrossRef]
38. He, Z.; Guo, W.; Zhang, P. Performance prediction, optimal design and operational control of thermal energy storage using artificial intelligence methods. *Renew. Sustain. Energy Rev.* **2022**, *156*, 111977. [CrossRef]
39. Inderwildi, O.; Zhang, C.; Wang, X.; Kraft, M. The impact of intelligent cyber-physical systems on the decarbonization of energy. *Energy Environ. Sci.* **2020**, *13*, 744–771. [CrossRef]
40. Sachs, J.D.; Schmidt-Traub, G.; Mazzucato, M.; Messner, D.; Nakicenovic, N.; Rockström, J. Six transformations to achieve the sustainable development goals. *Nat. Sustain.* **2019**, *2*, 805–814. [CrossRef]
41. Wu, J.; Zhang, J.; Tan, W.; Lan, H.; Zhang, S.; Xiao, K.; Wang, L.; Lin, H.; Sun, G.; Guo, P. Application of Time Serial Model in Water Quality Predicting. *Comput. Mater. Contin.* **2023**, *74*, 67–82. [CrossRef]
42. Yang, X.; Ran, G. Forecasting China's CO_2 emissions and identifying key drivers: An application of the improved RFAGM model and LMDI decomposition methods. *Int. J. Sustain. Dev. World Ecol.* **2024**, 1–14. [CrossRef]
43. Babatunde, D.E.; Anozie, A.N.; Omoleye, J.A. Artificial neural network and its applications in the energy sector—An overview. *Int. J. Energy Econ. Policy* **2020**, *10*, 250–264. [CrossRef]
44. Bashir, M.F.; Ma, B.; Hussain, H.I.; Shahbaz, M.; Koca, K.; Shahzadi, I. Evaluating environmental commitments to COP21 and the role of economic complexity, renewable energy, financial development, urbanization, and energy innovation: Empirical evidence from the RCEP countries. *Renew. Energy* **2022**, *184*, 541–550. [CrossRef]
45. Leal Filho, W.; Yang, P.; Eustachio, J.H.P.P.; Azul, A.M.; Gellers, J.C.; Gielczyk, A.; Dinis, M.A.P.; Kozlova, V. Deploying digitalisation and artificial intelligence in sustainable development research. *Environ. Dev. Sustain.* **2023**, *25*, 4957–4988. [CrossRef]
46. Mohammadi, E.; Alizadeh, M.; Asgarimoghaddam, M.; Wang, X.; Simões, M.G. A review on application of artificial intelligence techniques in microgrids. *IEEE J. Emerg. Sel. Top. Ind. Electron.* **2022**, *3*, 878–890. [CrossRef]
47. Yigitcanlar, T.; Cugurullo, F. The sustainability of artificial intelligence: An urbanistic viewpoint from the lens of smart and sustainable cities. *Sustainability* **2020**, *12*, 8548. [CrossRef]
48. Niazkar, M.; Goodarzi, M.R.; Fatehifar, A.; Abedi, M.J. Machine learning-based downscaling: Application of multi-gene genetic programming for downscaling daily temperature at Dogonbadan, Iran, under CMIP6 scenarios. *Theor. Appl. Climatol.* **2023**, *151*, 153–168. [CrossRef]
49. Marzban, N.; Libra, J.A.; Hosseini, S.H.; Fischer, M.G.; Rotter, V.S. Experimental evaluation and application of genetic programming to develop predictive correlations for hydrochar higher heating value and yield to optimize the energy content. *J. Environ. Chem. Eng.* **2022**, *10*, 108880. [CrossRef]