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Analysis of a multi-energy coupling model for rural energy under the rural digital economy

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Abstract

With the growth of the digital economy, the sustainable growth of rural energy has become crucial. However, traditional rural energy models have the drawback of not considering digital technology and renewable energy. Therefore, there is an urgent need for rational planning and development of rural energy. According to this, a multi-energy coupling model for rural energy systems was established by considering equipment capacity planning and operation scheduling optimization based on a multi-energy coupling structure. At the same time, considering the biomass resources in rural energy systems, an optimized configuration model for biomass coal-fired coupled power generation units was established. The results showed that the energy consumption cost in County A accounted for only 3.3%. County C focused mainly on tourism and emphasized economic efficiency, with investment costs 8.6% and 10.3% lower than other rural areas. The system utilized time of use electricity prices to optimize operation. The low storage stage was from 1:00 to 8:00, while the high incidence stage was from 12:00 to 14:00 and from 7:00 to 21:00. In the actual scenario, the multi-energy coupling model can be combined with intelligent technology to realize the real-time monitoring, prediction and optimal control of the energy system. Through the introduction of advanced digital technology, the model can be more flexible to deal with the diversified energy sources and complex operational scheduling situations involved in rural energy systems. This can improve the response speed and adaptability of the system, making the energy system more resilient and efficient.

Keywords: Digital economy, Rural energy, Multi-energy coupling, Typical scenarios, Reasonable planning

Introduction

In rural areas, with the rapid rise of the digital economy, in-depth research on the multi-energy coupling (MEC) model of energy utilization has become a hot topic in the current academic and industrial circles. By integrating interdisciplinary methods such as data science, energy economics, and information technology, it is possible to gain a more comprehensive understanding of the complex interrelationships between different forms of energy in rural areas (Vijay et al. 2022). However, under the current digital economy in rural areas, rural energy faces problems such as uneven development, low technological level, information asymmetry, and unstable energy supply (Cao et al. 2020). The current research mainly focuses on system modeling, operation strategy selection, optimization index selection and optimization methods. However, the research on energy system model construction, planning, configuration and operation optimization in typical rural scenarios is relatively insufficient. On the other hand, the MEC model serves as a model that comprehensively considers the interaction between multiple forms of energy. This type of model typically includes various forms of energy such as electricity, thermal energy, and gas, and achieves efficient integration of energy systems by coupling their production, conversion, transmission, and utilization processes (Usman and Abdullah 2023; Wu et al. 2023). The design of this model aims to maximize the overall performance of the energy system, optimize resource utilization, reduce environmental impact, and improve energy utilization efficiency (Decheng et al. 2023). Based on this, the study proposes to use a MEC model to systematically evaluate and optimize energy utilization in the context of rural digital economy, and to carry out equipment capacity planning and operation scheduling optimization. Meanwhile, considering the biomass resources in rural energy systems, the study also establishes an optimized configuration model for biomass coal-fired coupled power generation units. A two-layer algorithm is used to solve the programming analysis model. At the upper level, improved particle swarm optimization algorithms are used to deal with planning problems, mainly equipment selection and capacity optimization. YALMIP mixed integer linear algorithm is used to solve the problem of operation and maintenance layer. The upper and lower models are interconnected, and optimal planning ensures that the system can determine the best operational strategy. The research aims to provide scientific and quantitative support for rural energy planning and management. The study innovatively analyzes the rural energy MEC model and optimizes equipment planning and operation scheduling through digital technology. This study is composed of five parts. The first part introduces the research background, problems, and solutions of rural energy under the digital economy in rural areas. The second part summarizes the research achievements of rural energy under the digital economy in rural areas and the difficulties and shortcomings of methods. The third part introduces the design optimization method of the rural energy MEC model under the rural digital economy. The fourth part designs performance verification experiments to prove the performance of the proposed planning analysis model in empirical analysis of typical rural areas. The fifth part summarizes the research methods, analyzes the experimental results, and proposes the shortcomings and prospects of the methods.

Related works

The rural energy system under the digital economy in rural areas is showing a new development trend. Under the catalysis of digital technology, energy production, distribution, and consumption in rural areas are undergoing profound changes. Li and other researchers proposed to build a comprehensive energy system for rural electrification in China, with rural distribution networks as the core, by increasing the proportion of electricity consumption. The aim was to address the challenges of low efficiency and insufficient infrastructure in China's rural energy system. The experimental results indicated that this system provided suggestions for the growth of rural energy and references for the building of rural energy systems in similar countries (Li et al. 2021). Jarno et al. proposed using Analytic Hierarchy Process (AHP) to rank sustainable development standards, aiming to address the high dependence of Finland's heating sector on fossil fuels. The results indicated that age and education level had an impact on the respondents' emphasis on environmental standards and renewable energy (Raghu et al. 2023). Yimen et al. proposed integrating biomass power generation technology into distributed hybrid renewable energy systems, aiming to replace diesel generators, reduce system costs and environmental impacts. The results indicated that the integration of BPT could effectively reduce costs and promote sustainable development goals (Yimen et al. 2022). Li et al. used the biogas carbon emission trading plan as an example to explore the impact of internet access on farmers' willingness to participate in renewable energy electricity market incentive policies and their expectations for carbon prices, aiming to address the issue of farmers' willingness to participate in carbon markets and PCT plans. The results indicated that internet access increased farmers' willingness to participate in PCT programs and their expectations for carbon prices (Li et al. 2023). Pelz supported the Fair Energy Supply Improvement Program through data collection and analysis. It also described an effective method for collecting and analyzing spatially representative household energy access survey data. The study found that there were geographic and wealth-related inequalities in energy supply and related burdens. These results helped urban planners understand the scale and spatial dimensions of supply shortfalls, underscoring the importance of disaggregated measurement of transparent and equitable planning for energy supply improvement (Pelz 2020).

On the other hand, MEC cooperation is a model that integrates different energy types and systems together, which can comprehensively consider the interaction of different energy types and optimize the entire energy system. Some scholars have conducted relevant research on it. Witkowski et al. examined the technical characteristics of different thermal power generation technologies by analyzing data from seven actual project cases, aiming to address the challenge of the increasing share of renewable energy in modern power grids. The results indicated that the coupling of these technologies could improve their flexibility in the power grid (Witkowski et al. 2020). Researchers such as Hu et al. proposed a method based on heterogeneous data models, aiming at transforming the situational awareness problem of coupled networks into degree analysis of spectral differences of random matrices. The results indicated that the method was feasible and effective by verifying the changes under different conditions in the electro pneumatic coupling network (Hu et al. 2020). Cao and other researchers developed a price-based demand response driven multi-energy collaborative system optimization model, aiming at solving the problem of optimizing system operation modes to improve economic benefits. The results indicated that adopting these measures could significantly improve the economy of multi-energy collaborative systems (Cao et al. 2020). Chen et al. proposed a novel hybrid vibration energy harvester, aiming at addressing the issues of low energy conversion efficiency and narrow operating frequency band in traditional single frequency piezoelectric vibration energy harvesters. The results indicated that the new hybrid vibration energy harvester could operate over a wider frequency range and achieve multi-modal vibration energy harvesting (Chen et al. 2021). Hu et al. proposed a multidimensional electric-gas coupling network situational awareness method based on heterogeneous data models, aiming to address the problem that energy conversion between independent energy networks increases the complexity of situational awareness. The feasibility and effectiveness of the proposed method were proved by verifying the variation of different conditions in the electric-gas coupling network (Hu et al. 2020).

To sum up, there are some limitations in the study of rural energy models, including uneven resource distribution and high initial investment. At present, some scholars have proposed a series of solutions through the research of distributed energy system, biomass energy, biomass gasification and other methods. However, there are still challenges in the practical application of these methods. These include the coordination and management challenges of distributed energy systems, the sustainable supply and efficiency of biomass energy, and the technical difficulties and economic feasibility of biomass gasification. On the other hand, the MEC model can simulate the interrelationship, conversion and optimization process of a variety of different energy sources in the system, and it has strong potential application value to analyze and optimize various energy systems, such as smart grid, integrated energy system, urban energy planning, etc. Therefore, the design of rural energy MEC model under rural digital economy is of great significance, which is expected to provide strong support for smart grid, integrated energy system and urban energy planning.

Design of rural energy multi-energy coupling model

The research will combine data science, energy economics, and information technology, using interdisciplinary methods to comprehensively understand the complex relationships between different forms of energy in rural areas. The research aims to use a MEC model to systematically evaluate and optimize energy utilization in the rural digital economy environment, providing a basis for scientific and quantitative support for rural energy planning and management.

Modeling of differentiated development of rural energy models

Rural energy refers to the energy resources supplied and used in rural areas, whose characteristics and demands often differ from those in urban areas. Rural energy encompasses various forms of energy, including traditional biomass energy (such as firewood and straw), fossil energy (such as coal and liquefied petroleum gas), and renewable energy (such as solar and wind energy). These energy sources are widely used in rural areas for household life, agricultural production, and rural industries. Figure 1 shows the traditional rural energy supply model.

In Fig. 1, the traditional rural energy supply model usually adopts a decentralized and backward approach, mainly relying on traditional energy resources such as biomass energy (firewood, straw, etc.), fossil energy (coal, diesel, etc.), and a small amount of electricity supply. These supply methods face many challenges, including low energy utilization efficiency, resource waste, environmental pollution, and unstable energy supply. Meanwhile, due to limitations in technology and supply networks, traditional models are unable to meet the growing energy demand, hindering the sustainable development of rural areas (Naumann and Rudolph 2019; Nida and Grossner 2019). On the contrary, modern rural energy systems aim for comprehensive indicators and utilize advanced energy internet technology to comprehensively utilize distributed power generation methods (such as biomass energy, natural gas, and wind and light) combined

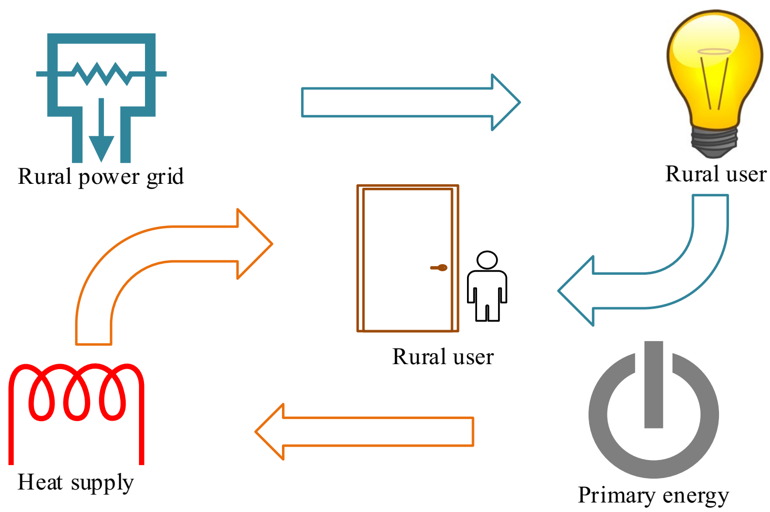

Fig. 1 Traditional supply mode of rural energy

Comparison item	Traditional rural energy supply	Rural energy system
Electric energy	Weak distribution network	Distributed generation equipment and distribution network complementary power supply
Heat energy	Burning primary energy	Electric heating unit, triple supply unit, geothermal heat pump
Clean energy	No	Clean energy, such as natural gas, and renewable energy, such as biomass, adjust their operation modes according to local demand
Running time	No clear distinction	Day (distributed power generation, triple power supply units): night (rural power grid, triple power supply units)
Security	Weak	Relying on a variety of power generation systems independent energy supply, safe and reliable
Economy	The cost of purchasing electricity is high	Balance power purchase and distributed unit output according to TOU price

Fig. 2 Comparison of two energy supply modes

with energy conversion equipment (such as cogeneration units, water heaters, and heat pumps) to achieve spatiotemporal complementarity of heterogeneous energy. This innovative energy supply architecture has the characteristics of clean, safe, low-carbon, and efficient, providing reliable energy solutions for rural areas. The comparison of energy supply methods between traditional and modern rural energy systems is shown in Fig. 2.

In Fig. 2, traditional rural energy supply methods usually rely on limited resources, such as biomass energy and a small amount of electricity supply, which have problems such as low energy efficiency, severe environmental pollution, and unstable energy supply. The modern rural energy system is based on the comprehensive utilization of multiple energy sources, utilizing advanced technologies such as energy internet to achieve spatiotemporal complementarity of heterogeneous energy, providing clean, safe, low-carbon, and efficient energy supply, which helps to improve energy utilization efficiency, reduce environmental impact, and promote sustainable rural development. The rural energy system provides different types of energy to terminals based on load demand by coordinating the coupled operation of various energy equipment (Calvert et al. 2021; Oh 2023). The system includes energy production and storage equipment, whose economic and technical parameters and performance affect system planning and optimization. Solar energy is the main renewable energy source. Photovoltaic (PV) panels convert light energy into electricity through semiconductor materials, and their output is affected by environmental conditions. The mathematical expression for output is shown in Eq. (1).

$$P_{PV,K,t} = \mathrm{P}^{stc}_{pv,k}\mathrm{G}_{AC,k,t} \cdot [1 + K_T(T_{c,k,t} - \mathrm{T}_r)]\big/\mathrm{G}_{Stc}. \tag{1}$$

In Eq. (1), G_{Stc} represents the light radiation density parameter (under standard test conditions). $\mathrm{G}_{AC,k,t}$ and $T_{c,k,t}$ represent the t time respectively, and $\mathrm{P}^{stc}_{pv,k}$ represents the maximum power generation under the marked test conditions of the kth PV panel. The actual radiation density of the kth PV panel and the actual ambient temperature of the PV panel. T_r and K_T respectively represent the rated reference temperature and rated power temperature coefficient of the PV panel. Rural energy usually uses multiple PV panels to construct a distributed PV power generation system, and its total power generation at t can be expressed mathematically as Eq. (2).

$$P_{PV,\ K,t} = \eta_{PV} \cdot H_S \cdot A_P \cdot N_1/G_{Stc}. \tag{2}$$

In Eq. (2), η_{PV} represents the conversion efficiency of a single PV panel. A_P represents the area of the PV panel. H_S represents the intensity of sunlight. N_1 represents the number of PV panels in the system. In general, certain areas in rural areas have a natural gas network structure, which can be utilized for energy conversion through natural gas systems (Li et al. 2021). The equipment output model of the system includes power generation models for gas turbines, gas internal combustion engines, and gas boilers (GBs). The mathematical model of the power generation output of a gas turbine can be denoted as Eq. (3).

$$P_{GT} = F_{GT} \cdot \eta_{GT} \cdot q_g. \tag{3}$$

In Eq. (3), F_{GT} and η_{GT} respectively represent the natural gas consumption and power generation efficiency of the gas turbine, while q_g represents the calorific value of natural gas. The mathematical expression for the output of waste heat generated by a gas turbine is shown in Eq. (4).

$$Q_{GT} = F_{GT} \cdot \eta^h_{GT} \cdot q_g. \tag{4}$$

In Eq. (4), η^h_{GT} represents the heating efficiency of the gas turbine. Compared to gas turbines, internal combustion engines have more complex power characteristics, but their working principles are similar. The mathematical expression for the power generation of internal combustion engines is shown in Eq. (5).

$$P_{GE} = F_{GE} \cdot \eta_{GE} \cdot q_g. \tag{5}$$

In Eq. (5), F_{GE} and F_{GE} respectively represent the power generation efficiency and natural gas consumption of gas internal combustion engines. The mathematical expression for the heating power of gas internal combustion engines is shown in Eq. (6).

$$Q_{GE} = F_{GE} \cdot \eta_{GT}^{h} \cdot q_g. \quad (6)$$

In Eq. (6), η_{GT}^{h} represents the heat generation efficiency. The mathematical expression for the output of a GB is shown in Eq. (7).

$$Q_{GB} = F_{GB} \cdot \eta_{GB}^{h} \cdot q_g. \quad (7)$$

In Eq. (7), F_{GB} represents the natural gas consumption of the GB. η_{GB}^{h} is the power generation efficiency of the gas turbine. The overall planning of rural energy systems can effectively address the complementary and coupling relationships of different energy sources, and compensate for the limitations of separate planning for heterogeneous energy sources (Baek and Baek 2024; Yong et al. 2021). Among them, solving the coupling relationship between multiple energy sources within the energy system is a key issue in overall planning. To address this issue, the study adopts an energy hub modeling method, which abstracts the energy hub as an input–output port model that describes the relationship between energy conversion and storage within the energy system, known as the black box model. The specific diagram is shown in Fig. 3.

In Fig. 3, the input–output port model of the energy system is an abstract description used to reveal the relationship between energy conversion and storage within the system. This model treats the energy system as a black box, with input ports representing the entry of energy and output ports representing the outflow of energy after system conversion. The energy input of an energy hub is represented by the P vector at the left end, while the energy output is represented by the L vector at the right end. Its mathematical expression can be succinctly expressed as Eq. (8).

$$L = f(P). \quad (8)$$

Based on the grey prediction model, the study improves the prediction method by introducing policy fluctuation terms to represent the impact of various policies on rural load. By analyzing load changes, a clear load boundary is provided for optimizing the coupling capacity of biomass and coal combustion. The policy fluctuation term is placed after the exponential growth result after quadratic fitting and mainly plays a role in the subsequent prediction part. Figure 4 shows the principle process of model prediction.

In Fig. 4, the basic model is first established by using the grey prediction model, and then improved through the quadratic fitting method and moving average method.

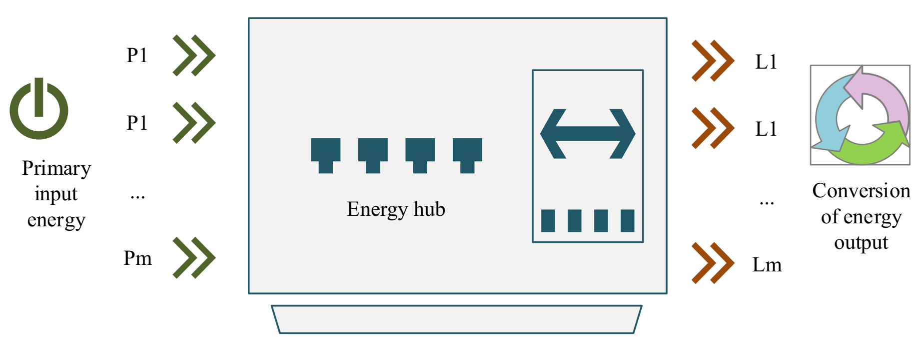

Fig. 3 Input–output port model of energy system

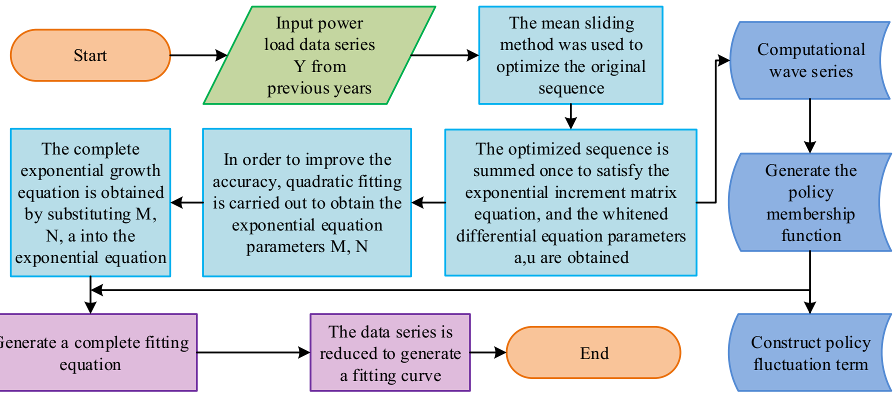

Fig. 4 Rural load forecasting process considering the impact of energy transition policies

Subsequently, the policy fluctuation term is introduced to characterize the impact of energy transition policies on load changes and integrated into the prediction model. Finally, by analyzing the model prediction results, a rural load prediction considering energy transition policy factors is obtained.

Design of a multi-energy coupling model for rural energy in the digital economy

This study focuses on rural biomass resources and further proposes a biomass coal-fired coupling power generation planning method to optimize the configuration of biomass boilers. At the same time, a two-level planning model considering differentiated energy development is established by integrating a multi-level rural energy hub model. The objective function F with the lowest comprehensive total cost is composed of the initial investment cost (f_1), operating cost (f_2), economic benefit (f_3), electricity price difference (f_4), and environmental benefit (f) of a biomass boiler coupled with coal-fired power generation. Its mathematical expression is shown in Eq. (9).

$$minF = \chi_1 \times (f_1 + f_2) - \chi_2 \times f_5 - \chi_3 \times (f_4 + f_5). \tag{9}$$

In Eq. (9), χ_1 represents the economic weight value. χ_2 represents the environmental weight value. χ_3 represents the energy-saving weight value. In the planning model, considering the large proportion of initial investment cost, the study converts the initial investment cost of equipment into an equal annual value through a discount rate. The investment and installation cost of biomass coupling equipment technology renovation is represented by Eq. (10).

$$f_1 = (B_{inv} \cdot S)\frac{D(1+D)^N}{(1+D)^N - 1}. \tag{10}$$

In Eq. (10), the investment cost per unit capacity of the biomass gasifier is expressed as B_{inv}. The planned unit capacity is S. The discount rate is D. The equipment life of the biomass gasifier is N years. The mathematical expression for the change in operating cost of coal-fired power generation units coupled with biomass gasifiers is shown in Eq. (11).

$$f_2 = (C_{mat,1} - C_{mat,2}) \cdot S. \tag{11}$$

In Eq. (11), $C_{mat,1}$ and $C_{mat,2}$ respectively represent the operating cost per unit capacity of coal-fired units before coupling and the operating cost per unit capacity of coal-fired units after coupling with biomass gasifiers. The mathematical expression for the standard coal consumption of coal-fired power generation units coupled with biomass gasifiers is shown in Eq. (12).

$$B_2 = H_1/(\eta_1 \times \eta_2 \times 29308). \tag{12}$$

In Eq. (12), the pipeline efficiency constant is η_2, and η_1 represents the thermal efficiency of the coal-fired boiler after coupling with the biomass gasification furnace. H_1 is the heat generation efficiency of coal-fired units. The mathematical expression for the standard coal savings after coupling a coal-fired boiler with a biomass gasification furnace is shown in Eq. (13).

$$\Delta B = \Delta b_q \cdot (p_i/1000) - \Delta B_f. \tag{13}$$

In Eq. (13), Δb_q represents the standard coal consumption for biomass gasification furnace power generation, and $\Delta b_q = (p_i/S_c) \cdot B_2$. At i time, the power generation of biomass gasification furnace is represented by p_i. The amount of standard coal increased before and after the coupling of coal-fired units is ΔB_f. The economic benefits achieved by coupling coal-fired units with biomass gasifiers come from the mathematical expression of the saved standard coal quantity, as shown in Eq. (14).

$$f = \Delta B \cdot (Y_1 - Y_2) \cdot T_A. \tag{14}$$

In Eq. (14), Y_1 and Y_2 respectively represent the price of standard coal and the recovery and treatment cost of biomass raw materials. T_A represents the average operating time of the unit. In the study, policy subsidies before and after coupling coal-fired units with biomass gasifiers will be included in the consideration of energy-saving costs in the form of Eq. (15).

$$f_4 = \sum_{T_A} P_i(I_C - I_B). \tag{15}$$

In Eq. (15), I_C and I_B respectively denote the on grid electricity price of biomass energy and the on grid electricity price of the original coal-fired unit. Further research will use Matlab optimization tools to optimize the total installed capacity of biomass coupled coal-fired units. The specific optimization is indicated in Fig. 5.

In Fig. 5, the capacity optimization of biomass coupled coal-fired power units involves first evaluating energy demand and resources to ensure reliable supply of biomass and coal. Then, considering technical and economic factors, including investment costs, operational efficiency, and environmental impact, it determines the optimal capacity configuration using simulation or optimization methods to achieve optimal resource utilization and cost minimization. Finally, system validation and risk assessment are conducted to ensure that the selected capacity scheme meets electricity demand, operates stably, and complies with environmental regulations. To

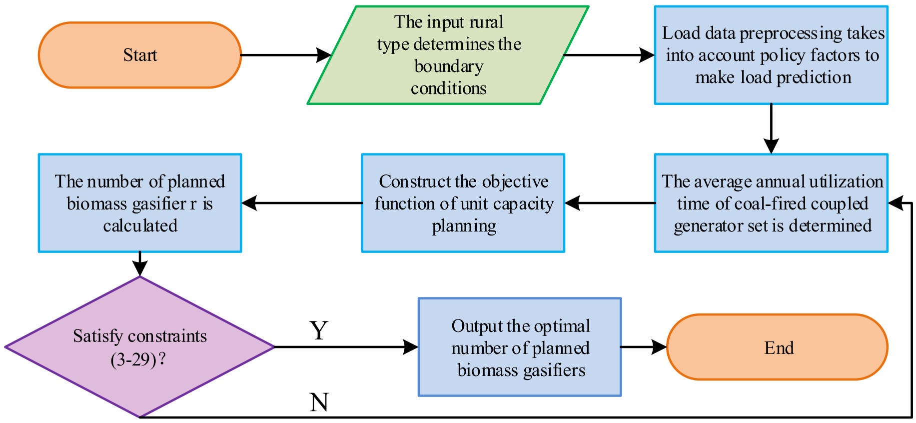

Fig. 5 Capacity optimization flow chart of biomass coupled coal-fired units

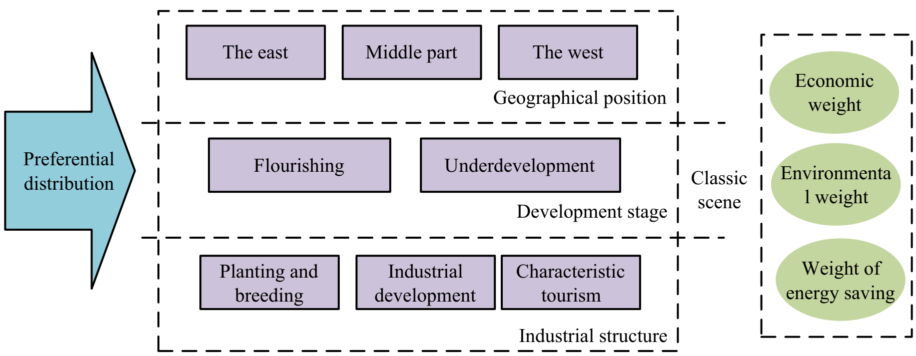

Fig. 6 Weight allocation process based on differentiated scenarios

improve the solving speed of rural energy system planning models, the study simplifies the impact of energy conversion equipment on efficiency operating characteristics. Introducing a load rate threshold, when the equipment load rate falls below this threshold, the system selectively stops the operation of the equipment to simplify the model and improve overall efficiency. In the planning of rural energy systems, considering the different focuses of energy transformation in different rural areas and the differences in demand for indicators among different rural areas, this article conducts research based on differentiated development scenarios. Figure 6 shows the process of weight allocation.

Figure 6 shows that weighting is used to consider the indicator needs of each rural area based on their energy needs and transition priorities. This ensures that energy system planning adequately meets the development needs of each region. The planning level involves three decision variables: the planned capacity of energy production equipment, the configured capacity of energy storage equipment, and the rated power of energy storage equipment. At the operational level, there are three decision variables: the input power of the energy system, the power of the energy storage equipment, and the energy distribution coefficient. A two-layer algorithm iteratively solves the programming analysis model. At the upper level, an improved particle swarm optimization algorithm is applied to deal with planning problems, mainly for equipment selection and capacity optimization. The YALMIP mixed integer linear algorithm is used in the lower layer to solve the operational level problem. The upper and lower models are interconnected, and optimal planning ensures the system can determine the best operational strategy.

Effectiveness analysis of multi-energy coupling models based on typical scenarios

By studying the differentiated development scenarios of rural energy, three typical rural areas with different development stages, geographical locations, and industrial structures were selected, combined with their characteristics and energy forms. On the basis of considering the MEC between various devices, the effectiveness of the constructed rural energy system planning and analysis model was verified.

Verification of biomass coal-fired coupled power generation capacity planning model

The biomass coal-fired coupled power generation capacity planning model proposed in the study took into account the results of energy transition policies in rural load forecasting as the boundary condition. A comparative simulation verification was conducted using the farming type A rural area in the central region and the industrial development type B rural area in the eastern region as examples. A dual-level planning optimization model for rural energy systems under MEC was studied, and a case study was conducted with corresponding parameters set A. The typical daily load of two types of rural areas is shown in Fig. 7.

According to Fig. 7a, the average power load in County A was around 7 MW, and the average heat load was around 10 MW. The daytime working hours were the main concentrated period for various load demands and usage, with peak load usually occurring in the afternoon, while low load values were relatively stable. According to Fig. 7b, the average power load in County B was around 9.5 MW, and the average heat load was around 6 MW, with significant changes in cooling load. County B generally had two peak periods, morning and noon, with the peak cooling load occurring during the daytime high temperature period and the peak heating load occurring at night. Figure 8 shows the daily wind speed and light intensity in three typical scenarios.

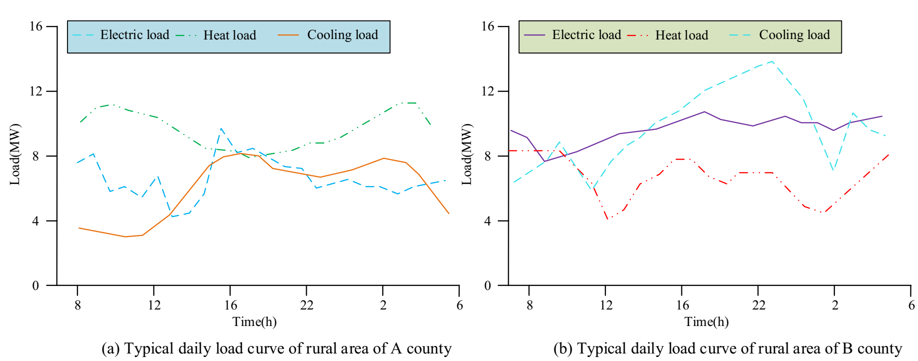

Fig. 7 Typical daily load of rural areas in types A and B

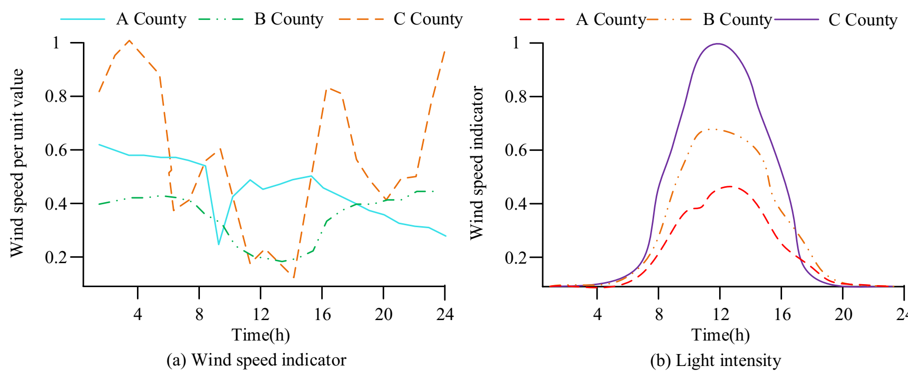

Fig. 8 Typical daily load curve of rural areas in C county

Table 1 Results of typical rural device configuration planning

Device type	WT	GB	EHP	AC	ELB	CCHP	PV	BAT
CASE 1	10	–	–	–	–	–	10	2.3
CASE 2	0	4.75	4.2	4.8	3.8	5.0 × 2	10	1.2
CASE 3	10	3.42	2.2	3.4	2.6	3.0 × 2	3.7	1.7

According to Fig. 8a, the average typical daily wind speed in County A was around 0.4, and the average typical daily wind speed in County B was around 0.3. The annual typical daily wind speed in County A was significantly higher than that in County B. According to Fig. 8b, the highest annual average light intensity per unit value in County C was 1, and the average light duration was the longest. The highest annual average light intensity per unit value in County B was about 6.5, and its typical sunlight intensity was stronger than that in County A.

Validation of the effectiveness of a multi-energy coupling model based on typical regions

According to research analysis, County A has adopted a hybrid scheme of wind and PV energy, utilizing the higher wind resources along its eastern coast. Due to its flat terrain and relatively low wind resources, County B mainly relied on PV power generation and has not planned wind turbines (WT). County C took into account both wind and solar power, as it has windy desert areas and longer average annual sunshine hours. In the planning, priority was given to the configuration of renewable energy generation units. Table 1 shows the planning results of typical rural equipment configuration.

According to Table 1, PV is solar photovoltaic, WT is wind turbine, CCH is distributed combined cooling and heating power production system, GB is gas boiler, ELB is electric boiler, EHP is electric pump, AC is air conditioning, BAT is battery, HST is thermal storage tank, CWS is cold water station. The configuration capacity of PV under CASE 1 was 3.7, and the configuration capacity of WT was 10. In CASE 3, the data showed that the configured capacities of PV and WT were both 10BAT. The economic cost and scenario economic analysis of three types of rural areas, after normalization of target weights, are shown in Fig. 9.

In Fig. 9, Cinv represents the initial investment cost of the rural energy system. Cmat represents the annual operating and maintenance cost of the equipment. Cenv

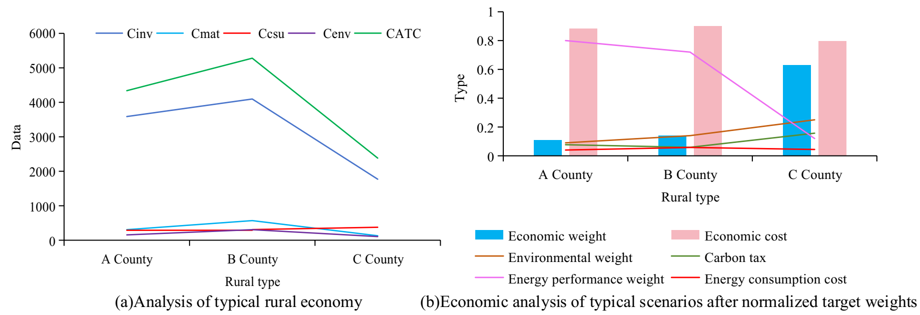

Fig. 9 Economic cost and scenario economic analysis of three types of rural areas after normalization of target weights

is the carbon emission cost generated by the energy system. CATC is the full life cycle cost considering the weighting factors of differentiated development scenarios. Ccsu is the energy cost. According to Fig. 9a, among the three county towns, the Cinv of Counties A, B, and C was 3587, 4096, and 1770, respectively. The highest Catc in County B was 5280. Overall, the various costs of County B, including raw material costs, capital service costs, environmental costs, and average total costs, were higher compared to the other two counties. According to Fig. 9b, the economic weight of Counties A, B, and C was 0.11, 0.14, and 0.63, respectively. The economic cost for Counties A, B, and C was 0.883, 0.900, and 0.797, respectively. Overall, the main industries in County A had high demand, developed economy, and focus on energy conservation, with energy consumption costs accounting for only 3.3%. County C focused on tourism and economy, with investment costs 8.6% and 10.3% lower than other rural areas. County A emphasized energy conservation and low costs. County C was economically cautious and had lower investment costs. Figure 10 further records the SOC balance of energy storage equipment in the rural energy system of County A.

According to Fig. 10a, the BAT in County A, also known as the battery, had a maximum remaining energy of 3.4 MWh. According to Fig. 10b, HST, also known as the water storage tank, had a maximum of 7.2 MWh. The electricity cycle was from 07:00 to 06:00 the next day. Between 01:00 and 08:00, it needed to purchase low-priced electricity to meet demand. From 09:00 to 24:00, priority would be given to PV and wind turbines for power generation. Figure 11 shows the dynamic energy storage balance of the rural energy system in County B recorded in the study.

According to Fig. 11a, the BAT in County A, also known as the battery, had a maximum remaining energy of 2.4 MWh. According to Fig. 11b, HST, also known as the water storage tank, had a maximum capacity of 9.2 MWh. Overall, the system utilized time of use electricity prices to optimize its operation. Electricity was purchased for charging during low electricity prices (1:00–8:00, low storage stage), and electricity was sold to the grid for discharge during high electricity prices (12:00–14:00 and 19–21:00, high generation stage). In other time periods, arbitrage through low storage and high issuance strategies was used to ensure the economic operation of the system. This flexible use of energy storage power stations enabled the system to achieve significant economic benefits in the face of electricity price fluctuations. The performance of the model was proposed for further verification. The study randomly

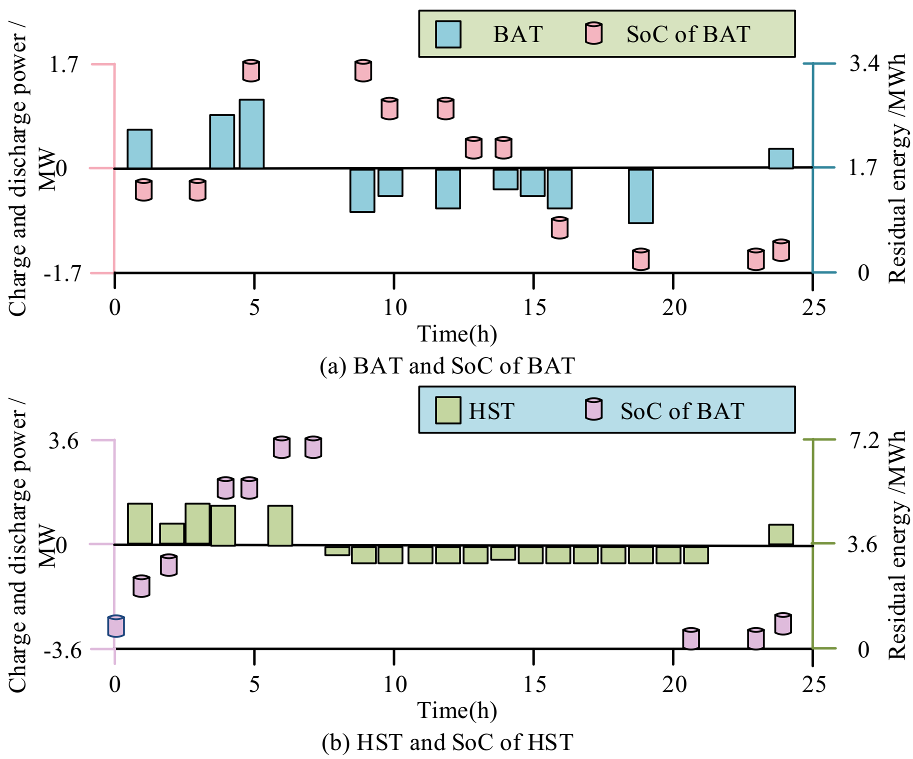

Fig. 10 SOC balance of energy storage equipment in rural energy system of County A

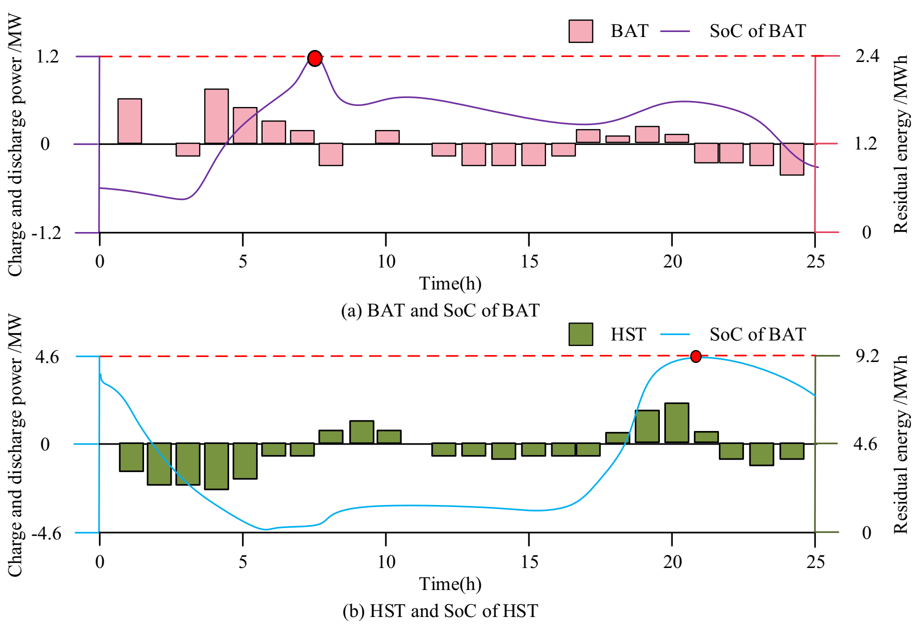

Fig. 11 SOC balance of the energy storage device in the rural energy system of County B

selected two scenarios to carry out the quantification results of operation benefits under multiple scenarios, among which, the scenario randomly selected for the study and scenario 2 was the quantification result of any model. Scenario 3 and Scenario 4

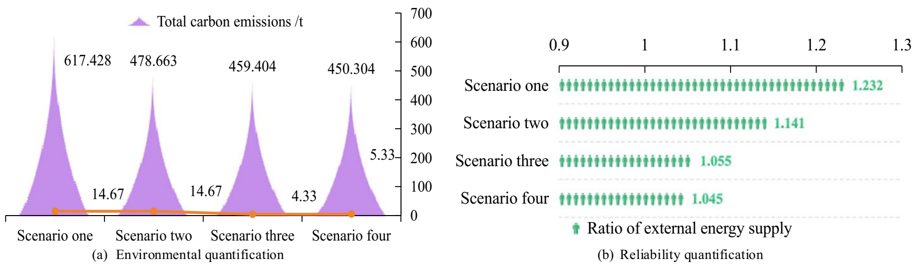

Fig. 12 Quantitative results of multi-scenario optimization operation benefits

were the results after using the MEC model proposed by the research. The specific results are shown in Fig. 12.

Fig. 12a is environmental quantification, and Fig. 12b is reliability quantification. From Fig. 12, in the two randomly selected scenarios, the quantification results of operation benefits reflected were better after the research model was used. The results showed that the proposed model could produce more economic and environmental benefits, which had great advantages and could realize the coordination of system benefits with user expenditure, economic benefits and environmental benefits.

Conclusion

With the rise of digital economy, rural areas are facing a comprehensive transformation, and rural energy management has become a key issue. At present, traditional rural energy models have shortcomings in handling the integration and application of renewable energy. Based on this, the study utilized a MEC model to optimize the energy utilization of rural digital economy, including equipment planning and operation optimization. Simultaneously considering biomass resources, an optimization model for biomass coal-fired power generation units was established, aiming to provide in-depth insights for rural energy management. The results showed that the average typical daily wind speed in County A was about 0.4, while in County B that was about 0.3. The annual typical daily wind speed in County A was higher than that in County B. The highest annual average light intensity per unit value in County C was 1, and the average light duration was the longest. The highest annual average light intensity per unit value in County B was about 6.5, and the typical sunlight intensity was stronger than that in County A. County B had two peak periods, morning and noon, with the peak cooling load occurring during the daytime high temperature period and the peak heating load occurring at night. The MEC model could simulate the advantages of the interrelationship, conversion and optimization process of various energy sources in the system, and solve the problems of coordination and management of traditional energy models, technical difficulties and poor economic feasibility of biomass energy gasification. Compared with the existing energy models, the research adopted a comprehensive method and HOMER simulation software, so that the model could more accurately consider the supply and demand relationship of various energy sources, and carry out economic and reliability analysis. The optimization of energy utilization in rural digital economy by MEC model has achieved remarkable results, especially in equipment planning and operation optimization. It is important to note that the planning of rural energy networks may be constrained in the face of the effects of energy system interactions and construction times. Future research should focus on multi-regional integrated energy systems, adapting to the rapid evolution of the digital economy through phased collaborative planning. In addition, the impact of renewable energy uncertainty on system planning needs to be considered more deeply. In implementation, researchers need to carefully address the complexity of the energy system and develop flexible strategies to meet possible challenges to ensure the long-term effectiveness and viability of the model in the digital economy environment.

Author contributions
HL contributed to the motivation, the interpretation of the methods, the data analysis and results, and provided the draft versions and revised versions, references. XL has participated sufficiently in the work to take public responsibility for the appropriateness of the method, and the collection, analysis, and interpretation of the data.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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