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Spatiotemporal evolution of investment-carbon emission coupling coordination in China's electricity market

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Promoting the low-carbon development of the electricity market is the key to controlling CO_2 emissions and achieving carbon neutrality in China. It requires the coordinated development between investment and carbon emissions in the electricity industry. Based on the panel data on electricity investment and carbon emissions from 2000 to 2019, this study systematically explains the coupling coordination mechanism between electricity investment and carbon emissions. We use the coupling coordination model to calculate the coupling coordination degree of each province. Then, the research uses the GM (1, 1) model to predict the coupling coordination development from 2020 to 2030. The study finds that the development of China's electricity industry is in good shape. Although the coupling coordination degree has entered barely or primary coordination in most provinces, there are certain fluctuations in recent years; there are spatial differences in coupling and coordinated development among regions: the central region has a high coupling coordination degree, while the eastern and northeastern regions are relatively lagging behind. In the next 10 years, the coupling coordination degree will continue to grow, and all regions will reach the primary coordination. Among them, the central region will reach the intermediate coordination.

KEYWORDS

electricity industry, carbon emission (CE), spatiotemporal evolution characteristic, coupling coordination degree, gray system analysis

Introduction

As the proportion of electricity in global terminal energy consumption rises, electricity is gradually replacing other non-renewable energy sources. It gradually becomes the core leading the low-carbon transformation of the energy system. Due to an over-reliance on fossil fuels for electricity production, the share of the electricity industry in global CO_2 emissions has increased year by year. It has already surpassed all other sources of CO_2 emissions from energy activities. According to *Global Energy and CO_2 Status Report 2018* released by the International Energy Agency (IEA), the global electricity industry emits 13 billion tons of CO_2, accounting for 38% of the total energy-related CO_2 emissions. Nearly two-thirds of the increase in energy-related CO_2 emissions comes from the contribution of the electricity industry. Under the trend of electrification of the global economy, the use of carbon is flowing across industries, resulting in an increase in carbon emissions in the electricity industry. From a global perspective, the electricity industry is an important source of carbon emissions in the carbon trading market. Thus, strengthening investment, promoting clean energy transformation, and accelerating the expansion of renewable energy power generation have become effective ways to achieve carbon emission reduction in the electricity industry (IEA, 2018).

According to an IEA report, China's power and thermal energy sector generated 4.747 billion tons of CO_2 in 2018, accounting for 49.6% of the country's total CO_2 emissions. Faced with severe environmental pollution, China has been actively optimizing the investment structure of the electricity industry, contributing significantly to the promotion of green and low-carbon development. Affected by global COVID-19, China's electricity industry has undergone major changes in recent years. Electricity investment has declined and continues to show a downward trend (IEA, 2020). At the moment, China's electricity market is still in its initial stages, and its carbon emission reduction potential is not fully stimulated. In this context, exploring the relationship between China's electricity investment and carbon plays a positive role in promoting the construction of the electricity industry. It is beneficial to the overall development of China's electricity enterprises, reduces carbon emissions, and steers electricity investment on a more environmentally friendly path.

There is a close relationship between investment and carbon emissions in the electricity industry. However, the coupling coordination between them has not been systematically studied. Therefore, based on the coupling perspective, this study studies their interaction mechanism and discusses the differences in the coupling coordination degree from the inter-provincial level. In order to better understand future development, we also forecast the coupling coordination degree. It can provide a scientific basis for the construction of the electricity industry and the coordinated development of the system so as to promote the coupling and coordinated development of the electricity market at different levels and scales.

Literature review

The increasing environmental concerns have led the world to rethink alternative and innovative ways to harness clean energy. Technology and infrastructure, economy and finance, politics and system, culture and behavior, meteorology, and other factors are all factors that hinder its development (Irfan et al., 2022). As traditional non-renewable energy sources such as coal, oil, and natural gas produce a large amount of greenhouse gases, there is unprecedented interest in the increasing supply of renewable energy sources (Kok et al., 2018). With the growth of the economy, the energy problem and the environment deteriorate. The problem of energy consumption structure becomes more and more serious. The generation of renewable energy is crucial for achieving sustainable development (Wei et al., 2022). The amount of investment in renewable and non-renewable energy should be determined by the electricity market. Renewable energy generation technology has a high generation investment cost (Aflaki and Netessine, 2017). Although lowering the investment cost of renewable power generation technology is a key factor to promote the low-carbon transformation, the traditional nonrenewable energy investment is still important. The low investment cost of these energy sources can provide a more reliable electricity supply than renewable energy sources while requiring fuel expenditure and carbon emission costs (Kis et al., 2018).

The use of fossil fuels can be reduced by technological innovation in the electricity industry. In the production process, clean technologies replace the original polluting technologies. In the long run, it will significantly improve the operation efficiency and contribute to low-carbon development (Lee, 2013; Daniel-Gromke et al., 2018). In addition, Internet development and entrepreneurship also help improve the efficiency of green innovation (Fan g et al., 2022). However, in view of natural uncertainties (e.g., climate sensitivity) (Fuss et al., 2012; Turner et al., 2017; Wang et al., 2021), market uncertainty (e.g., energy price fluctuation) (Pahle et al., 2013; Hirth, 2018), technical uncertainty (e.g., the feasibility of new technology) (Gnansounou et al., 2004; Castillo and Linn, 2011), socioeconomic uncertainty (e.g., COVID-19 epidemic impact) (Zhong et al., 2020; Haxhimusa and Liebensteiner, 2021; Iqbal et al., 2021), and policy uncertainty (e.g., hedging strategy, investment tax credit, cash subsidy, etc.) (Morris et al., 2018; Braungardt et al., 2021), it is difficult to evaluate the importance of different technologies in achieving a steady investment to reduce carbon emissions. A key issue for policymakers is how to allocate limited funding across multiple technologies, balancing R&D investment to drive innovation in emerging low-carbon technologies (Santen et al., 2017).

The essence of both the electricity market and carbon market is to achieve low-cost, clean, and low-carbon development. Electricity investment and carbon emissions influence each other through the interaction. Investment in the electricity industry has dual effects on carbon emissions: on the one hand, with the increase in investment, the economic scale of the electricity industry expands unceasingly. Under the condition that the technological level, industrial structure, and emission coefficient remain unchanged, a large amount of energy consumption leads to an increase in carbon emissions (Zhao et al., 2016; Peng et al., 2018); on the other hand, investment can affect carbon emissions through the efficiency path.

Technological investment improves the efficiency of energy processing, thereby reducing carbon emissions in production (Jin et al., 2017). On the premise of ensuring energy supply, reasonable investment is conducive to optimizing the electricity market structure, improving energy utilization efficiency, and controlling and reducing carbon emissions (Ma and Liu, 2018).

At the same time, the carbon market information will also be fed back to the investment of the electricity industry. The carbon market will increase the economic burden of low-efficiency and high-carbon electricity enterprises, while the high-efficiency and low-carbon electricity enterprises can obtain economic benefits through the carbon market. A large amount of money is used to create new renewable technologies to reduce its dependence on fossil fuels (Xia et al., 2020). Energy prices should provide real costs associated with the growing problem of environmental pollution (Li et al., 2021). As the main body of regional emission reduction, enterprises are most concerned about their own profits. Emission reduction requires a lot of human, material, and financial resources, which will reduce its output to a certain extent. Therefore, the enthusiasm of enterprises to reduce emissions is not high.

To promote corporate emission reductions, governments around the world have implemented various low-carbon policies. As one of the common carbon emission reduction policies, the carbon cap and trade mechanism imposes carbon quotas on companies that rely on carbon emissions, thereby forcing companies to engage in research and development of emission reduction technologies (Sun et al., 2020). When carbon emissions are too high, the government needs to adjust regulatory incentives to encourage enterprises to increase their investment in low-carbon electricity technologies and give appropriate subsidies and tax exemptions to low-carbon enterprises (Schafer, 2019; Chen et al., 2021). Additionally, the carbon emission trading system and carbon emission quota allocation rules have an impact on how the electricity industry invests, under the carbon emission trading system. When an enterprise's carbon emissions exceed those set by the government, it will increase investment in renewable energy technologies to lower the cost of the carbon trading market's quotas (Zhou et al., 2010).

Coupling coordination mechanism

There is a potential trade-off between carbon emission reduction and investment. Reducing carbon dioxide emissions will bring huge economic losses to China. Controlling greenhouse gases can only be achieved by reducing the energy use, adjusting the energy structure, and controlling population growth. Mitigation measures should focus on industrial structure transformation (Jin et al., 2020). At the same time, carbon emissions also have social costs, and the price of carbon dioxide to reduce emissions to the optimal level for the society must be carefully assessed (Bressler, 2021). Under the emissions trading scheme, there is a coupling relationship between investment and carbon in the electricity industry, and they interact and restrict each other.

According to Grossman and Krueger, (1995), carbon emissions are mainly affected by the scale effect, technology effect, and composition effect of electricity investment. The three factors are complementary to each other to a certain extent. On the one hand, the economic scale and industrial structure can influence the direction of technological progress on carbon emissions. With the upgrading of industrial structures and the expansion of the economic scale, technological progress promotes carbon emissions more than inhibiting them, which eventually leads to an increase in CO_2 emissions. On the other hand, technological progress will also strengthen the relationship between the economic scale, industrial structure, and carbon emissions. The three effects are as follows:

(1) The scale effect refers to the influence of investment in the electricity industry on carbon emissions by expanding economic activities. With the continuous increase of electricity output, the electricity industry needs more factor inputs. The electricity investment improves the industrial benefits, but it has also brought about an increase in carbon emissions at the same time (Shahbaz et al., 2022).
(2) The technology effect refers to that electricity investment can affect carbon emissions through the efficiency path. Electricity investment can promote innovation in the electricity industry, and technological progress can improve the utilization efficiency of non-renewable energy sources and reduce carbon emissions (Li and Li, 2020).
(3) The composition effect refers to the impact of electricity investment on carbon emissions by affecting the energy structure. As we all know, due to the characteristics of various energy varieties, different energy sources release different carbon emissions (Burnham et al., 2012). The investment plays a role in guiding and regulating the allocation of resources and directly affects the structure of energy production. If limited funds are invested in the production of high-pollution and high-emission energy projects, it will lead to an increase in carbon emissions. If the funds are invested in the production of clean energy projects with low pollution and low emission, it will be beneficial to reduce carbon emissions by improving the energy structure (Li and Qi., 2011).

The scale effect can be offset by the technology effect and the composition effect. When the scale effect dominates, the

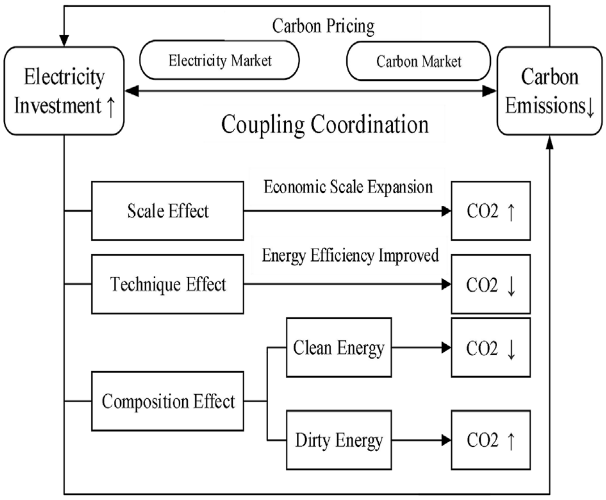

FIGURE 1
Coupling coordination mechanism of investment and carbon emission.

environmental pollution will increase. When the technology effect and composition effect of clean energy dominate, the environmental quality will be improved. In general, the scale effect and technology effect typically necessitate some degree of economic development. The nation and enterprises can make significant investments and realize independent technological innovation. At the same time, the carbon market will also backfire on electricity investment. The government will introduce policies to intervene in order to meet existing emission reduction targets. Carbon pricing is an effective policy tool to regulate the investment structure of the electricity industry. It can provide more opportunities for electricity enterprises to invest in clean resources. Once carbon pricing is in place, the non-renewable energy sources will be abandoned. The resource portfolio will become cleaner, leading to greater emissions reductions (Oggioni and Smeers, 2012; Fan et al., 2014; Petitet et al., 2016).

The degree of market development for carbon emissions has an important impact on carbon pricing investment. Initially, because of the reasonable setting of the actual emission cap of enterprises, the carbon market did not generate significant costs. Instead, the carbon market system started out modestly. With the continuous improvement of carbon emissions, the price of carbon will increase. This will encourage enterprises to actively step up their efforts to reduce emissions and invest more in renewable energy sources (Aflaki and Netessine, 2017). When investments increase and carbon emissions continue to decline, the electricity market and the carbon market will achieve good coupling coordination. The coupling coordination mechanism is shown in Figure 1:

Measurement of the coupling coordination degree

Coupling coordination model

Based on the coupling coordination mechanism, we further use the coupling coordination model to quantify it. The term “coupling” originally belongs to the concept of physics, which refers to the phenomenon that two or more systems interact with each other and have mutual influence. It is often used in the field of economics to judge whether the development of variables is orderly. Compared with other methods, the coupling coordination model has a strong advantage in studying the interaction and coordinated development of subsystems. It is intuitive and easy to explain. Coupling contributes to the development of the joint forces among the systems, which not only promotes the self-development of each subsystem but also strengthens the coordination of each subsystem. The model does not need to select too many control variables. If there are too many control variables, too many systems will interfere with the final result. Since the level of the coupling degree value cannot accurately reflect the coordinated development level, this study establishes a coupling coordination model. The specific steps are as follows:

Normalize the data by min-max, and remove the unit limitation to the data. Also then, convert it into a dimensionless pure value so that indicators of different units or magnitudes can be compared. For the positive indicator of electricity investment, the normalization formula is as follows:

$$x_{it}^{'} = \frac{x_{it} - \min x_i}{\max x_i - \min x_i} \quad 1 \leqslant i \leqslant n \quad 1 \leqslant t \leqslant T \tag{1}$$

For the reverse indicator of carbon emission, the normalization formula is as follows:

$$x_{it}^{'} = \frac{\max x_i - x_{it}}{\max x_i - \min x_i} \quad 1 \leqslant i \leqslant n \quad 1 \leqslant t \leqslant T \tag{2}$$

x_{it} is the original data on the *ith* province in the *tth* year, $x_{it}^{'}$ represents the standardized result of the *ith* province in the *tth* year, and max x_i and min x_i are the maximum and minimum values of the indicator, respectively. According to the coupling coordination model, the coupling degree is calculated through the standardized $x_{it}^{'}$, and the formula is as follows:

$$A = \frac{2\sqrt{f(I)g(C)}}{f(I) + g(C)} \tag{3}$$

A represents the coupling degree between investment and carbon emissions in the electricity industry, $f(I)$ represents the investment level, and $g(C)$ represents the carbon emission level. The value ranges from 0 to 1. The larger the value, the higher the coupling degree is. When $A = 1$, it represents the optimal coupling state between the two markets. Since the coupling

TABLE 1 Classification of the coupling coordination degree.

Coupling coordination degree interval	Coupling coordination degree	Coupling coordination degree interval	Coupling coordination degree
$0 \le D < 0.1$	Extreme disorder	$0.5 \le D < 0.6$	Barely coordination
$0.1 \le D < 0.2$	Severe disorder	$0.6 \le D < 0.7$	Primary coordination
$0.2 \le D < 0.3$	Moderate disorder	$0.7 \le D < 0.8$	Intermediate coordination
$0.3 \le D < 0.4$	Mild disorder	$0.8 \le D < 0.9$	Well coordination
$0.4 \le D < 0.5$	Verge of disorder	$0.9 \le D \le 1$	Quality coordination

degree can only reflect the coupling degree between systems, the coupling coordination model is further introduced:

$$F = \alpha f(U) + \beta g(C) \tag{4}$$

$$D = \sqrt{A \times F} \tag{5}$$

F represents the comprehensive coordination index; α and β represent the weight coefficients. Assuming that they have the same importance to the system as a whole, both α and β are set to 0.5. Referring to empirical research practices (Chen et al., 2019; Cui et al., 2019; Zhou et al., 2020), the coupling coordination degree is divided into ten grades. The classification standards are shown in Table 1.

Data source

This study mainly analyzes the coupling coordination degree of investment and carbon emissions in China's provincial electricity industry from 2000 to 2019. The investment data on the electricity industry come from the National Bureau of Statistics of China and *the China Energy Statistics Yearbook*. In view of the lack of official data on carbon emission of the electricity industry in each province, this study adopts the carbon emission data on China's electricity industry calculated by Carbon Emission Accounts and Datasets (CEAD), by referring to relevant international data recommended by the Intergovernmental Panel on Climate Change (IPCC). These data are based on the *2006 IPCC Guidelines for National Greenhouse Gas Inventories*, and the carbon emission intensity of China's electricity industry is measured by the energy balance table, which has been widely used in related fields. From the perspective of data availability, 30 provinces in China were selected as the research objects. Because CEAD has not released the carbon emission data on Tibet, Hong Kong, Macau, and Taiwan, these regions are not included in the calculation.

Result analysis

Although the carbon emissions of all provinces have increased in recent years, the size is different (Table 2). From the perspective of the average carbon emissions in the electricity industry, Shandong, Jiangsu, Inner Mongolia, and other provinces have relatively high carbon emissions with an annual average of more than 300 Mt. The average annual carbon emissions of Hebei, Shanxi, Henan, and Guangdong also exceed 200 Mt, while the carbon emissions of first-tier developed provinces such as Beijing and Shanghai are relatively low. The standard deviation in Inner Mongolia and Shandong is large, while that in Hainan, Qinghai, Beijing, and Shanghai is small. At the same time, there is a strong positive correlation between investment and carbon emissions. Provinces with high carbon emissions also have larger investments. Hebei, Inner Mongolia, and Shandong have maintained high investment; their investment is much higher than that of low carbon emission areas.

Figures 2, 3, respectively, show the mean value and growth rate of investment and carbon emissions in the electricity industry in China's provinces from 2000 to 2019. During the investigation period, carbon emissions increased year by year, and the growth rate of carbon emissions decreased significantly since 2010. Although there has also been a significant increase in electricity investment, the growth has been sluggish in recent years. In 2018, there was negative growth. There is great room for improvement.

According to Eqs 1–5, the coupling coordination degree of investment and carbon emissions of 30 provinces in China each year can be calculated (Table 3). Due to space limitations, only the calculation results of 2000, 2010, and 2019 are shown to investigate the changing trend of the coupling coordination degree with time. From 2000 to 2019, the coupling coordination degree has increased significantly in all provinces. At the beginning of the new century, except for a few provinces and regions such as Zhejiang and Hubei, most provinces were facing a disorder state. There is an imbalance between electricity investment and carbon emissions. The provinces in the state of mild imbalance and on the verge of imbalance account for 40%, respectively, while some provinces such as Hainan were still in a state of severe imbalance.

As time goes on, the coupling coordination degree in each province has improved significantly. In 2010, most provinces have gotten rid of the maladjustment state. They entered the

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TABLE 2 Descriptive statistical results.

Region	CO_2 (Mt)		Investment (100 million)		Region	CO_2 (Mt)		Investment (100 million)	
	Mean	Std. Dev	Mean	Std. Dev		Mean	Std. Dev	Mean	Std. Dev
Beijing	32.38	5.30	142.76	96.15	Henan	211.66	59.72	608.73	561.95
Tianjin	50.17	17.24	173.27	112.18	Hubei	106.61	32.19	408.39	204.39
Hebei	227.04	73.49	730.52	647.27	Hunan	80.48	27.30	353.99	227.52
Shanxi	202.67	86.65	507.51	357.36	Guangdong	228.72	67.40	714.39	391.10
Inner Mongolia	303.44	171.01	842.43	528.83	Guangxi	57.19	25.47	347.84	233.39
Liaoning	178.75	50.10	365.68	236.13	Hainan	13.09	7.11	60.9	50.31
Jilin	92.06	21.48	258.4	170.96	Chongqing	42.08	14.17	209.49	118.37
Heilongjiang	106.9	31.59	253.11	149.18	Sichuan	62.12	14.08	732.63	465.78
Shanghai	63.58	8.11	132.91	50.95	Guizhou	92.57	31.31	242.09	88.25
Jiangsu	307.49	113.36	610.82	410.54	Yunnan	49.72	22.22	532.29	317.96
Zhejiang	188.92	58.40	504.86	257.08	Shaanxi	97.65	44.42	394.18	319.03
Anhui	140.36	62.46	348.1	277.23	Gansu	60.91	22.82	325.05	256.74
Fujian	91.95	39.32	423.39	271.97	Qinghai	11.13	3.50	194.39	183.67
Jiangxi	63.28	27.08	231.56	179.68	Ningxia	70.53	50.29	204.12	193.83
Shandong	349.77	147.94	813.51	763.52	Xinjiang	119.64	94.97	515.42	558.46

FIGURE 2
Carbon emissions of China's provinces from 2000 to 2019.

stage of reluctant coordination and primary coordination. Among them, Sichuan has even entered the stage of intermediate coordination. Although Hainan is still in the stage of mild imbalance, it still has a significant increase. Beijing, Shanghai, and other developed provinces are still on the verge of imbalance, and the coupling and coordinated development are not satisfactory. In 2019, the coupling coordination degree has achieved a further leap in some provinces. Henan has made the most obvious progress. However, some provinces have not increased. The coupling coordination degree is facing a state of imbalance again, showing an "inverted U-shaped" trend of change.

In order to further analyze the coupling and coordinated development of investment and carbon emission in different regions, this study divides 30 provinces into four parts, according to the geographical location: eastern, central, western and northeastern. Among them, the eastern region includes 10 provinces, namely, Beijing, Fujian, Guangdong, Hainan,

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FIGURE 3
Electricity investment of China's provinces from 2000 to 2019.

TABLE 3 Results of coupling coordination.

Region	2000	Level	2010	Level	2019	Level
Beijing	0.33	Mild disorder	0.46	Verge of disorder	0.51	Barely coordination
Tianjin	0.32	Mild disorder	0.50	Barely coordination	0.57	Barely coordination
Hebei	0.48	Verge of disorder	0.60	Barely coordination	0.76	Intermediate coordination
Shanxi	0.43	Verge of disorder	0.57	Barely coordination	0.60	Primary coordination
Inner Mongolia	0.32	Mild disorder	0.70	Primary coordination	0.26	Moderate disorder
Liaoning	0.40	Verge of disorder	0.65	Primary coordination	0.57	Barely coordination
Jilin	0.36	Mild disorder	0.61	Primary coordination	0.50	Verge of disorder
Heilongjiang	0.38	Mild disorder	0.58	Barely coordination	0.58	Barely coordination
Shanghai	0.41	Verge of disorder	0.49	Verge of disorder	0.45	Verge of disorder
Jiangsu	0.49	Verge of disorder	0.50	Barely coordination	0.56	Barely coordination
Zhejiang	0.51	Barely coordination	0.56	Barely coordination	0.63	Primary coordination
Anhui	0.38	Mild disorder	0.54	Barely coordination	0.61	Primary coordination
Fujian	0.45	Verge of disorder	0.62	Primary coordination	0.67	Primary coordination
Jiangxi	0.37	Mild disorder	0.53	Barely coordination	0.61	Primary coordination
Shandong	0.50	Verge of disorder	0.50	Verge of disorder	0.45	Verge of disorder
Henan	0.44	Verge of disorder	0.55	Barely coordination	0.81	Well coordination
Hubei	0.52	Barely coordination	0.59	Barely coordination	0.68	Primary coordination
Hunan	0.41	Verge of disorder	0.56	Barely coordination	0.71	Intermediate coordination
Guangdong	0.48	Verge of disorder	0.67	Primary coordination	0.72	Intermediate coordination
Guangxi	0.41	Verge of disorder	0.56	Barely coordination	0.68	Primary coordination
Hainan	0.15	Severe disorder	0.38	Mild disorder	0.49	Verge of disorder
Chongqing	0.35	Mild disorder	0.53	Barely coordination	0.57	Barely coordination
Sichuan	0.45	Verge of disorder	0.73	Intermediate coordination	0.78	Intermediate coordination
Guizhou	0.38	Mild disorder	0.54	Barely coordination	0.55	Barely coordination
Yunnan	0.37	Mild disorder	0.70	Primary coordination	0.70	Primary coordination
Shaanxi	0.40	Mild disorder	0.57	Barely coordination	0.68	Primary coordination
Gansu	0.36	Mild disorder	0.65	Primary coordination	0.56	Barely coordination
Qinghai	0.23	Moderate disorder	0.42	Verge of disorder	0.69	Primary coordination
Ningxia	0.24	Moderate disorder	0.52	Barely coordination	0.49	Verge of disorder
Xinjiang	0.34	Mild disorder	0.59	Barely coordination	0.58	Barely coordination

TABLE 4 Coupling coordination degree of four regions.

Year	Eastern	Level	Central	Level	Western	Level	Northeastern	Level
2000	0.41	Verge of disorder	0.43	Verge of disorder	0.35	Mild disorder	0.38	Mild disorder
2001	0.40	Verge of disorder	0.41	Verge of disorder	0.36	Mild disorder	0.37	Mild disorder
2002	0.39	Mild disorder	0.42	Verge of disorder	0.38	Mild disorder	0.36	Mild disorder
2003	0.40	Verge of disorder	0.42	Verge of disorder	0.40	Mild disorder	0.37	Mild disorder
2004	0.39	Mild disorder	0.38	Mild disorder	0.36	Mild disorder	0.34	Mild disorder
2005	0.48	Verge of disorder	0.50	Barely coordination	0.48	Verge of disorder	0.41	Verge of disorder
2006	0.48	Verge of disorder	0.52	Barely coordination	0.51	Barely coordination	0.45	Verge of disorder
2007	0.48	Verge of disorder	0.53	Barely coordination	0.52	Barely coordination	0.49	Verge of disorder
2008	0.50	Barely coordination	0.55	Barely coordination	0.54	Barely coordination	0.56	Barely coordination
2009	0.54	Barely coordination	0.56	Barely coordination	0.58	Barely coordination	0.58	Barely coordination
2010	0.53	Barely coordination	0.56	Barely coordination	0.59	Barely coordination	0.62	Primary coordination
2011	0.53	Barely coordination	0.55	Barely coordination	0.59	Barely coordination	0.59	Barely coordination
2012	0.55	Barely coordination	0.55	Barely coordination	0.61	Primary coordination	0.61	Primary coordination
2013	0.56	Barely coordination	0.58	Barely coordination	0.64	Primary coordination	0.61	Primary coordination
2014	0.59	Barely coordination	0.60	Primary coordination	0.67	Primary coordination	0.61	Primary coordination
2015	0.59	Barely coordination	0.65	Primary coordination	0.69	Primary coordination	0.57	Barely coordination
2016	0.61	Primary coordination	0.69	Primary coordination	0.68	Primary coordination	0.55	Barely coordination
2017	0.62	Primary coordination	0.69	Primary coordination	0.63	Primary coordination	0.59	Barely coordination
2018	0.59	Barely coordination	0.67	Primary coordination	0.60	Primary coordination	0.58	Barely coordination
2019	0.58	Barely coordination	0.67	Primary coordination	0.60	Barely coordination	0.55	Barely coordination

Hebei, Jiangsu, Shandong, Shanghai, Tianjin, and Zhejiang; the central region includes 6 provinces, namely, Anhui, Henan, Hubei, Hunan, Jiangxi, and Shanxi; the western region includes 11 provinces, namely, Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, and Yunnan; and the northeastern region includes three provinces, namely, Heilongjiang, Jilin, and Liaoning.

Among the four major regions, the coupling coordination degree of the central and western regions shows a better development state than the other two regions. After 2014, the average value of coupling coordination in the central region basically reached the primary coordination level and dropped slightly in 2018–2019. The western region has a low degree of coupling coordination at first, but the growth trend is good and it has basically reached the primary coordination state in recent years. Since 2010, the coupling coordination degree of the eastern and northeastern regions has shown an "inverted U-shaped" change. With the weak investment and the increase in carbon emissions in the electricity industry, the coupling coordination degree has shown a downward trend, especially in the northeastern region. The coupling coordination degree dropped from 0.62 in 2010 to 0.55 in 2019, falling from primary coordination to barely coordination again. The same development trend also existed in the eastern and western regions (Table 4).

Coupling coordination degree prediction

Based on the investment and carbon emission data from 2000 to 2019, this study further uses the GM (1, 1) model to predict the coupling coordination degree of each province from 2020 to 2030. Due to the limited sample size, the whole coupling coordination degree trend cannot be predicted by ordinary linear or nonlinear models with high uncertainty. In the gray system theory, the GM (1, 1) model is the most widely used coupling coordination degree prediction (Xing et al., 2019; Cheng et al., 2019; Wang et al., 2020). Under fewer data samples, the GM (1, 1) model makes full use of time-series data information for analysis and prediction. Compared with simulation prediction methods such as Markov chains and cellular automata, this method is more convenient to calculate and has higher prediction accuracy (Liu et al., 2018; Ye et al., 2022).

Suppose there are n observations and the original data time series of each province is $A_0 = [a_0(1), a_0(2), \cdots, a_0(n)]$, accumulate A_0 to obtain a new time series $A_1 = [a_1(1), a_1(2), \cdots, a_1(n)]$. Construct matrix $\boldsymbol{B}$、$\boldsymbol{Y_n}$, and the differential equation corresponding to the GM (1, 1) model is as follows:

$$\frac{dA_1}{dt} + aA_1 = u. \tag{6}$$

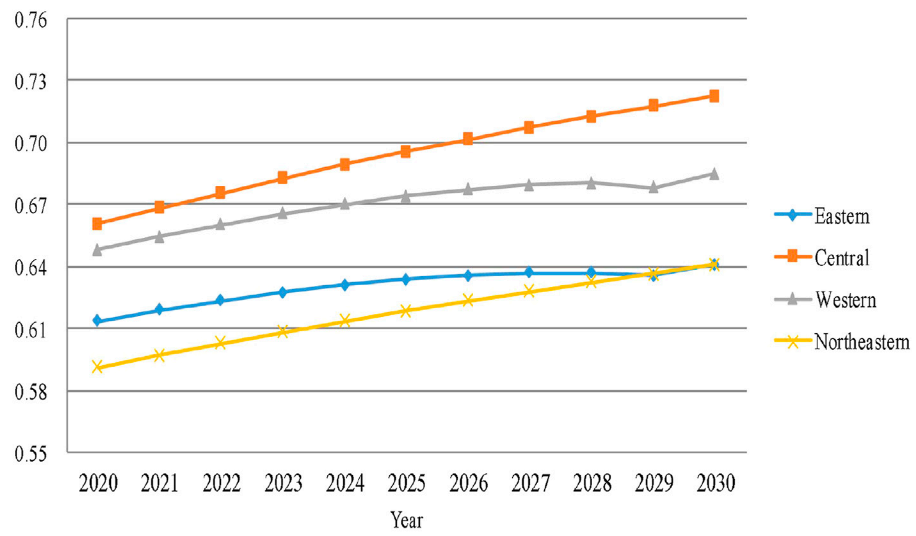

FIGURE 4
Prediction of the coupling coordination degree from 2020 to 2030.

a is the development gray level, u is the endogenous control gray number, and $\hat{a}$ is the parameter vector to be estimated. Using the OLS method to solve $\hat{a} = a/u$, we can get $\hat{a} = (B^T B - 1)B^T Y_n$; solve the differential equation to get the GM (1, 1) prediction model:

$$a_1^{\mathrm{T}} \hat{A}_1 (k+1) = \left[a_0(1) - \frac{u}{a}\right] e^{-ak} + \frac{u}{a} \quad k = 1, 2, \cdots, n. \tag{7}$$

By substituting the existing data into the GM (1,1) model, the predicted value of the coupling coordination degree can be obtained from Eq. 7. Figure 4 shows the predicted value of the coupling coordination degree in the four regions from 2020 to 2030. The coupling coordination degree in the central region shows the best performance. After 2025, the degree of coupling coordination reached the intermediate level, showing a rising trend. The coupling coordination degree in the western region has also increased steadily, but the growth rate is slightly lower than that in the central region, and it will continue to remain in the primary coordination stage in the next 10 years. In contrast, the development of the coupling coordination between the eastern and northeastern regions is relatively slow. After 2028, the coupling coordination degree of the two has achieved convergence, but there is still a certain gap in intermediate coordination.

Overall, the coupling coordination degree has been developing in a better direction, but the rising rate still needs to be further improved. Favorable policies and measures are needed to promote the high-quality coupling coordination development between electricity investment and carbon emissions across the country and in various provinces.

Conclusion and policy implications

Conclusion

China's electricity industry is in a critical transition period. The coordinated development of investment and carbon emissions will have a profound impact. Based on the investment-carbon emission system theoretical mechanism, this study calculates the coupling coordination degree and uses GM (1, 1) to predict them from 2020 to 2030. The conclusions are as follows:

(1) The coupling coordination degree of investment-carbon emissions in China's electricity industry is increasing steadily, and most provinces and regions have entered the stage of barely coordination and primary coordination.
(2) There are differences in the coupling and coordinated development of the electricity industry in different regions. The coupling coordination degree in the central region has the best development, while the coupling coordination degree in the eastern and northeastern regions is relatively backward. Although the coupling coordination degree of each region has shown good development, it has declined to a certain extent in recent years.
(3) According to the forecast results of the GM (1, 1) model, China's electricity industry will still show a good coupling and coordinated development trend in the next 10 years. The coupling coordination degree in the central region can reach the intermediate level, while the coupling coordination

degree in the eastern and northeastern regions rises slowly, which still needs to be focused on.

This study provides a new perspective for research on the relationship between investment and carbon emissions in the electricity industry, which makes up for the current lack of paying attention to investment and carbon emission reduction in isolation. It theoretically reveals the mechanism of action between electricity investment and carbon emissions, discusses the spatiotemporal evolution trend of the degree of coupling and coordination between the two, and enriches the relevant research on carbon emissions in the electricity industry. The research methods and framework also have a certain reference value for other industries with the same characteristics. The prediction of the coupling coordination degree provides a reference for China's electricity industry to formulate technological innovation and energy policies. It will help to better achieve the emission reduction goals under the low-carbon background of the "carbon peak" in 2030 and "carbon neutrality" in 2060.

Policy implications

The mismatch between investment and carbon emissions will hinder the development of the electricity industry. Provinces with different coupling coordination degree types need to formulate different strategies. For the provinces with high carbon emissions but low coupling coordination, their electricity industry relies too much on energy consumption in the development process. They lack sufficient technical support in the optimization of resources and the environment, which leads to the uncoordinated electricity investment and carbon emission system in these provinces. For these provinces, it plays an important role in promoting R&D and innovation of electric power technology; for provinces with low carbon emissions and a high coupling coordination degree, these places have developed economies, low dependence on carbon emissions, and relatively coordinated performance in dealing with the relationship between electricity investment and low-carbon development. Therefore, the electricity industry should pay attention to the improvement of existing emission reduction technologies and the development of new technologies.

In the future, it can be seen that there will still be differences in the coordination degree of investment-carbon emission coupling of the electricity industry in different regions. Further research is needed to realize the coordinated development of the two systems. The eastern, central, western, and northeastern regions should strengthen international technical exchanges, cooperation, and sharing and promote the rational utilization and optimal allocation of nationwide electricity investment. They should promote the coupling and coordinated development of the eastern and northeastern regions on the basis of consolidating the good achievements of the central and western regions, narrowing the difference of coupling and coordination between different regions, learn from the excellent regional development experience to form a demonstration effect, and jointly promote the energy conservation and emission reduction in the electricity industry.

Data availability statement

Publicly available datasets were analyzed in this study. These data can be found at: https://www.ceads.net.cn/.

Author contributions

YZ: methodology, data processing, formal analysis, and writing—original draft preparation. HZ: methodology, data processing, formal analysis, and writing—original draft preparation. FH: conceptualization, funding acquisition, and project management. All authors contributed to the manuscript and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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