Energy Strategy Reviews 51 (2024) 101304

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

Electricity generation and CO_2 emissions in China using index decomposition and decoupling approach

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ARTICLE INFO

Handling Editor: Dr. Mark Howells

Keywords:
Electricity generation
CO_2 emissions
Tapio's decoupling
LMDI
China

ABSTRACT

Over the past three decades, energy and economic growth have been joined by enormous environmental pollution and growing global concerns. It is necessary to check the factors' effects impacting CO_2 emissions and decouple CO_2 from economic growth for the biggest emitter China. This study uses the logarithmic mean Divisia index extended by introducing electricity substitution factors (i.e., activity, population, electricity intensity, electricity overall, generation structure, energy efficiency, and fuel emission factor effects) and is then combined with Tapio's decoupling method to analyze the CO_2 emission drivers, states and sectorial emissions for the years 1991–2020. The findings show that: (1) population and activity effects are the main driving factors in increasing CO_2 emissions by adding trade and electricity generation structure effects. (2) Decoupling states presented the two decoupling states through electricity CO_2 emissions and economic growth effects, showing that expansive negative decoupling is dominant. This shows that both factors show an increasing return to scale. (3) Individual factors and sectorial decoupling indexes show long-run variations and relationships between them, which means that industrial structure adjustment will help mitigate CO_2 emissions and sustain economic development. Finally, based on empirical findings, the results suggest more ambitious targets for emerging low-carbon technologies that could help the rapid decarbonization of China's electricity sector.

1. Introduction

Climate change adaptation and mitigation are two of the enormous challenges facing the world in the twenty-first century. Understanding and incorporating climate change factors (i.e., fuel emissions, energy substitution, economic sustainability, etc.) are necessary for developing strategies to mitigate risks and improve energy efficiency [1]. As per the International Energy Agency (IEA) [2], the share of the world's electricity in total energy consumption was counted at 24,901.4 TW h (TWh) in 2020, which historically declined by 155 TWh in 2019 due to COVID-19. Certainly, concerning fossil energy-based electricity generation systems, it is obvious that direct greenhouse gas (GHG) emissions are integral to their operations. However, technologies, for instance, renewable energy-related plants, may still be liable for a considerable amount of indirect carbon emissions, which encourages policies for enhancing the energy-saving efficiencies of these paths [3]. Therefore, it is necessary to properly measure the impacts of various driving factors used in electricity generation, aiming to check CO_2 emissions intensity and follow the most sustainable energy alternatives.

China's electricity sector is associated with huge CO_2 emissions due to the significant consumption of fossil fuels. Around 53.34 % of the overall CO_2 emissions of China come from electricity and heat, with a huge share among the GHG [4], which has encouraged the reduction of CO_2 emissions in the electricity generation sector. For this, the global community has significantly tried to reduce CO_2 emissions by 2 °C until the end of this century and challenge climate change through the Agreements in Paris. Also, the most rigorous goals of energy consumption and CO_2 emission were put forward in the 13th Five-Year National Plan of China, including that CO_2 emissions and energy intensity would be lessened by 18 % in 2015 and 15 % in 2020, respectively. Moreover, the National CO_2 emission trading market construction plan under the power generation industry approved in 2017 introduced a carbon trading system in China, and electricity generation was also part of this plan. Besides, China is moving into the mid-later phase of industrialization, and electricity demand is expected to sustain a steady rate of growth perspectives [5,6]. To attain the climate and energy efficiency

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https://doi.org/10.1016/j.esr.2024.101304
Received 27 March 2023; Received in revised form 11 December 2023; Accepted 10 January 2024

targets, the expression "on-grid" includes mini-macro grids.

The relationship between industrial sectors, economic growth, and global warming has long been given attention by O'Brien and Leichenko [7], profit and loss due to temperature increases [8] and heat-related damages to health negatively impact the productivity of solar energy industry workers [9], but China's electricity demand would grow by about 58.6 % under climate change by 2050 [10]. Moreover, few studies have revealed that a huge changeability of temperature destabilized sustained economic growth in China [11–13]. As per the World Energy Outlook [14], China will remain the biggest coal consumer and add 40 % of the global coal demand by 2040, which might be due to the coal-based resource endowment that defines the coal-dominated energy mix. Electricity generation permits stable supply, a central heating system, regulation, cost impact, and CO_2 emissions. However, the government of China has encouraged the growth of renewable energy, i.e., nuclear, solar, wind, and hydroelectricity, in which fossil fuel electricity structures are still dominant[1]with corresponding levels of CO_2 emissions. Approximately overall CO_2 emissions from the electricity sector are generated by coal consumption because the production process of renewable energy does not generate CO_2 directly [15]. Therefore, China's coal electricity generation is facing extreme pressure to undertake CO_2 emission mitigation responsibilities [16,17].

To mitigate the CO_2 emissions from electricity generation and achieve China's emissions reduction guarantee, a comprehensive analysis is needed to check the key drivers behind the CO_2 emissions and carry-out sound policy suggestions. The reduction in CO_2 emissions, showing the ecological burdens, should, however, permit economic development [18,19]. Hence, there have been indication-based frameworks suggested by Song et al. [20], Feng et al. [21], Qu et al. [22], and Li et al. [23] to widely investigate the performance of the economies concerning desirable and undesirable outputs. The conversion towards clean energy has been taken as an interesting pathway for lessening environmental degradation and economic development [24–26]. China is the largest developing economy in the world, and the stability between economic growth, the industrial revolution, and environmental considerations is imperative. Following the idea of a low-carbon economy, the energy-related carbon emissions due to electricity generation must be analyzed along with the dynamics of economic activity. Thus, these directives plan directions for energy security, accessibility, electricity affordability, and ecological protection in China. However, sustainable development, social welfare, and climate change mitigation are combined under the renewable and substitution policies determined by China's 13th renewable energy development five-year plan (2016–2020) [27]. It sets directions for non-fossil energy to increase by 15 % by 2020 and by 20 % by 2030 and awards consumers the right to consume, save, and increase output.

The consciousness of electricity conservation and CO_2 emission mitigation goals needs not only an all-inclusive estimation but also the development and progress of distinguished CO_2 emissions mitigation policies on sectorial and regional designs. These kinds of measures can fully knock CO_2 emission reduction possibilities in various countries and quicken low-carbon and renewable-development. China's maximum electricity is generated through fossil fuels, which presents a strong reliance of the power sector on fossil fuel resources [14]. Since energy is the major input for economic development, attaining higher economic growth requires raising the quantity of inputs or their productivity. To attain this objective, it is of a great emphasis for China to recognize the major factors and their decouplings at sectorial and national levels. Thus, this paper aims to reach the following objectives: (a) explore the main driving factors influencing the CO_2 emission from electricity generation in China; (b) check the effects of the decoupling phenomenon based on driving factors and at the national level; and (c) identify the effects of sectorial decoupling indexes on electricity consumption and value-added.

This study contributes to the following aspects: as for the research measure, this paper is the first to conduct the decomposition, decoupling state and the long-linear relationship between CO_2 emissions and electricity driving factors in China and its sectorial levels over the period 1990–2020, addressing the gap in past studies about this measure. This will give the local government empirical proof to comprehend the decoupling status and can support policymakers in framing precisely targeted evaluations for enhancing electricity efficiency and mitigation potential at national and sectorial levels. Respecting research, the current study is distinguished from presenting research that concentrates only on decomposition and decoupling states between CO_2 emissions and economic development. Thus, this paper analyzed the electricity-related CO_2 emission factors, such as population, activity, intensity, overall electricity, electricity generation, energy efficiency, and fuel emission factor effects, more comprehensively. This analysis will give reasonable and wide-ranging recommendations for the administration for framing CO_2 emission reduction targets and strategies. Regarding methodologies, such as logarithmic mean Divisia index (LMDI), decoupling and vector error correction models, this study analyzes the relationship between major driving factors during the Five-Year Planning period and on an annual basis for China and its sectors, which will help governments set possible energy-economic targets and productive estimations for starting low-carbon progress in the various sectors. This analysis achieved in this study can also be extended to developing countries and, to a greater degree, to other contaminants.

The remaining part of the study is as follows: Section 2 describes the literature review; Section 3 provides the data statistics; and Section 4 provides the method used. Section 5 provides empirical results and discussion, while Section 6 includes the conclusion and policy suggestions.

2. Literature review

Recently, the increasing proportion of CO_2 emissions due to electricity generation has drawn much attention. A study branch aims to discover the drivers of electricity CO_2 emissions, where decomposition and econometric models are commonly applied as the best tools. For example, Zhao et al. [28] investigated that industrial productivity had the largest impact on CO_2 emissions; Gong et al. [29] pointed out that the GDP and energy have positive impacts on various provinces of China, while electricity generation productivity impacted CO_2 emissions from electricity generation [1,30].

The current issues have been sightseen using impacting factors, which are leading or mitigating the CO_2 emissions in various developed and underdeveloping countries, for example, Andreoni and Galmarini [31] analyzed the economic growth and energy intensity factors for Italy and found that these factors are the major contributors to the rise in CO_2 emissions; Ang and Su [32] analyzed using electricity generation, carbon intensity and energy substitution for Globe and found that CO_2 emissions can be reduced by technological enhancement; Kim and Kim [33] found that fossil fuel mix in electricity generation causing the rise in CO_2 emissions in Korea; Rodrigues et al. [34] and Cansino et al. [35] used renewable electricity, fossil electricity production and electricity consumption for European Union and Spain and found that CO_2 emissions can only be reduced through renewable energy sources and technologies. Similarly, Mohlin et al. [36] for the United States, Raza and Dongsheng [37] for Pakistan's carbon source and carbon damage, Wang and Jiang [38] for BRICS countries, and Russo et al. [39] for Portugal found that electricity efficiency and mitigation potential can be enhanced by renewable resources and energy technologies. The above literature shows the main observations, such as the methodologies employed in past studies on CO_2 emissions from electricity generation through renewable and non-renewable energy sources, GDP and technologies as recommendations. However, they did not give exact

[1] The installed capacity of various electricity generation projects in China from 1991 to 2020 is provided at IEA [4].

evidence on the seven major driving factors we used and sectorial information under the decomposition and decoupling approach.

Moreover, few researchers have estimated the decomposition and decoupling analysis at different scales or in various regions. For example, numerous scholars have analyzed the decomposition and decoupling analysis all over China [40–51]. Other scholars have directed studies on the decomposition analysis in more specific sectors, for instance, transport, industry, residential, construction, power, provincial, and city-level [52–58]. However, studies on decomposition, decoupling and log-linear analysis in electricity generation and CO_2 emissions in China using the major driving factors at the national and sectorial are scarce, except for a few industrial studies with varying driving factors. For example, Wang et al. [52] for the provincial power sector of China from 2000 to 2019, analyzed that maximum decoupling has been seen between coal, gas, and renewable energy in Gansu province; Raza and Tang [54] found that technological factors are useful in the Pakistan from 1986 to 2019; Ma et al. [56] used the housing economic indicators with overall fuel consumption in the residential sector of China from 2001 to 2016. They analyzed that economic and energy factors added to the reduction in CO_2 intensity. Moreover, Xu et al. [57] analyzed the energy and CO_2 emissions in the cement sector of China from 1990 to 2009 and found that cement production succeeded in economic growth, particularly in the infrastructure and construction processes. Based on their analysis, we found three common drivers in several studies, such as energy, CO_2 emissions and economic growth, which left a big gap for the current study.

In conclusion, existing studies give much proof of the association between energy, CO_2 emissions and economic growth; however, a few flaws still exist (i.e., electricity generation factor (i.e., coal, oil and gas), energy efficiency, and fuel emission factor effects in the current period, especially at the national and sectorial levels), which the study tries to address. (1) The current study mainly concentrates on estimating electricity generation and carbon mitigation in China and sectors; however, few studies have examined industrial, cement, residential, provincial, and power sectors. China is considered by different economic progress and natural resource endowments across regions, and a one-size-fits-all CO_2 emissions mitigation policy is not valid in all sectors, however, it can be estimated to provide exact figures for policymakers. (2) Past studies have primarily measured the decomposition and decoupling methods, or linear models, to check the status between CO_2 emissions and economic development from an individual perspective. In fact, various indicators, such as energy intensity, activity, and carbon intensity, have a large impact on decoupling outcomes, fronting to uncertainty about outcomes.

Consequently, the current study finds the carbon emissions from electricity generation and its decoupling relationship with various factors and sectors in China from 1990 to 2020 in a more comprehensive way. The LMDI, Tapio's decoupling and autoregressive distributive lag models are adopted to investigate the major driving factors. Moreover, the empirical findings of current research can give practical proof to support the Chinese government comprehend the decoupling and linear status at the country and sectorial level. For multinational playmakers (i.e., the Paris Agreement), current research could also be favorable to framing indeed targeted policies for buildings that are energy-efficient and CO_2 emission mitigating policies and applying these policies to multinational policymakers.

3. Methods and data collection

3.1. Theoretical framework

In the background of electricity generation and CO_2 emissions, the six major factors are estimated using the decomposition and decoupling approaches. To better understand the causes of CO_2 emission variations, a new method of theoretical decomposition analysis based on data envelopment analysis can be proposed [59]. Similarly, based on index decomposition analysis under the LMDI, we can quantify the underlying factors that bring variations in different indicators, which give valuable information to policymakers. For this, the current study incorporated China's national and sectoral policy perceptions into the framework. The theoretical framework is shown in Fig. 1. In the analytical framework, socio-economic and energy variables have been established to significantly impact electricity-related CO_2 emissions. Like past studies, we employed electricity generation-related information and attitudes towards carbon mitigation for environmental protection and sustainable economic growth [42,60]. Furthermore, this model proposes that positive policy insight can raise productivity, which in turn raises policy effectiveness. This means that economic worth, carbon mitigation, and technological enhancement can enhance their motivation to collaborate with the policy, which ultimately saves electricity. Thus, we believe that the various factors employed in the decomposition and decoupling methods will affect electricity generation.

3.2. The LMDI decomposition method under the measurement of CO_2 emissions from electricity generation

The decomposition method is one of the most generally applied techniques to investigate the potential drivers of variations in CO_2 emissions [61]. This method is the best due to its theoretical basis, ease of use, and adaptation [62]. Moreover, the characteristics and advantages of the LMDI method can be seen in the studies of Wang et al. [63] and Ang and Goh [64]. The present study applies the LMDI method to decompose the factors for China's electricity generation, which is imperative for the sustainable development of different sectors by establishing a long-term relationship between electricity and related factors. In formulating the process, we suppose that the outcome under the decomposition process, for instance, C_e is the electricity-related CO_2 emissions. Assume that there are n factors contributing to variations in C_e overtime and each is linked with a computable variable, whereby there are n variables, such as $z_1, z_2, z_3 ... z_n$. Suppose sub-script i be a sub-category of the aggregate for which structural variation is to be calculated. For this, the sub-category level the association $C_{e,i} = z_{1,i}, z_{2,i}, z_{3,i} ... z_{n,i}$ holds. The general index identity is provided by $C_e = \sum_i C_{e,i} = \sum_i z_{1,i}, z_{2,i}, z_{3,i} ... z_{n,i}$, while the aggregate changes from $C_e^0 = \sum_i C_{e,i} = \sum_i z_{1,i}^0, z_{2,i}^0, z_{3,i}^0 ... z_{n,i}^0$ in time zero to time t. Thus, the time t formulation can be as: $C_e^t = \sum_i z_{1,i}^t, z_{2,i}^t, z_{3,i}^t ... z_{n,i}^t$. In the multiplicative decomposition, we decompose the ratio: $d_{total} = \frac{C_e^t}{C_e^0} = d_{z1}, d_{z2} ... d_{zn}$. A limitation of multiplicative synthesis is that it is only valid when the number of indicators is large and the assigned weights are relatively consistent [65]. Similarly, the difference can be decomposed as $\Delta C_{e_{total}} = C_e^t - C_e^0$ which is provided below in detail in Eq. (3). In the LMDI method, the general formula for the effect of the t factor on the right-side of Eqs. (1) and (2) are provided. We now present a general formula to decompose the CO_2 emissions from electricity generation as follows:

$$C_e^t = pop_t . \frac{gdp_t}{pop_t} . \frac{oec_t}{gdp_t} . \frac{iep_t}{oec_t} . \sum_i \frac{pge_t}{iep_t} . \frac{ifr_t}{pge_t} . fef_t \tag{1}$$

$$C_e^t = p_t . ae_t . eie_t . eoe_t . \sum_i gse_t . eee_t . fefe_t \tag{2}$$

where, C_e^t shows CO_2 emissions from electricity consumption; gdp_t shows the gross domestic value; pop_t shows the total population; oec_t indicates the overall electricity consumption; iep_t indicates the indigenous electricity production. Also, indigenous production means the share of the country's fuel (i.e., oil, coal, gas, and renewables) in electricity generation; pge_t represents the percentage of generated electricity; ifr^t shows input fuel ratio; fef_t indicates fuel emission factor, e is electricity, i is number of factors, and t is the time of estimation. Moreover, to check the

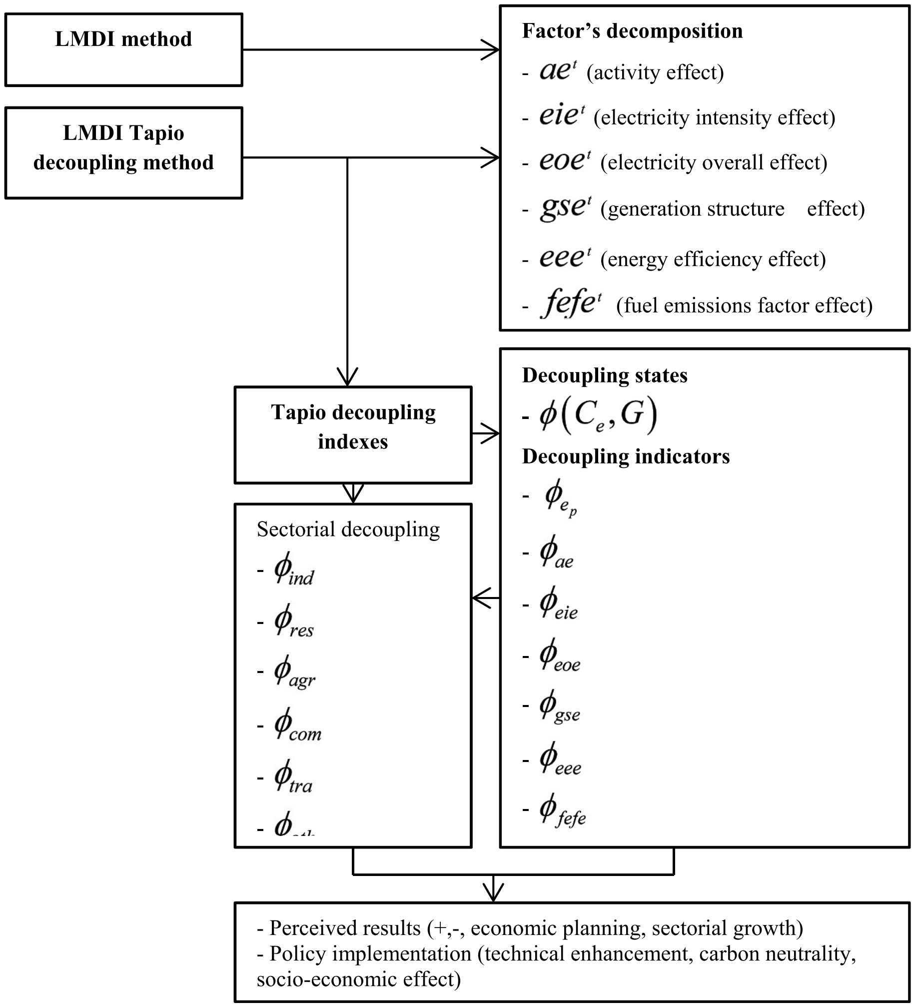

Fig. 1. Study framework for decomposition and decoupling approach.

relationship between driving factors, such as C_e^t and other environmental factors could be individually indicated as: p_t is population effect; ae_t indicate the activity effect; eie_t indicate electricity intensity effect; eoe_t show electricity overall effect; gse_t show generation structure effect; eee_t show energy efficiency effect, and $fefe_t$ indicate fuel emissions factor effect. To estimate each factor's effect, the assumptions show that:

The first entry on the right-side of Eq. (2) is known as population. If the numerical value is higher, the effect on carbon emissions will be higher. The second entry is called the activity effect ($ae^t = \frac{gdp_t}{pop_t}$) which presents that if the numerical-value is higher, the scale of the economy will also be at its maximum. This shows that the source of revenue will be productive. The third entry ($eie^t = \frac{oec_t}{gdp_t}$), presents that a lower numerical-value is beneficial. The fourth entry ($eoe^t = \frac{iep_t}{oec_t}$) shows that if the numerical-value is positive, the country has increased the level of electricity production, which will impact energy substitution towards a low-carbon transition. The fifth entry ($gse^t = \frac{pge_t}{iep_t}$) shows that if the numerical-value is positive, the ratio of electricity is rising. This is a sign of energy growth in the country due to various resources. The sixth entry ($eee^t = \frac{ifr_t}{pge_t}$) presents that if the numerical-value is higher, the country's generation is expanding, i.e., the expansion of fuel is raising the share of electricity. The seventh entry ($fef_t = fefe^t$) shows that if the numerical-value is lesser, the emissions factor will be lower. This also presents fuel efficiency and technological performance in lowering emissions. This will be more effective, and the consumption structure will be good if the amount is '0' or the use of fossil fuel is close to '0'.

Based on key driving factors, the C_e^t from [0-t] period can be decomposed as in Eq. (3).

$$C_e^t = C_e^1 - C_e^0 = \Delta C_{e\ p} + \Delta C_{e\ ae} + \Delta C_{e\ eie} + \Delta C_{e\ eoe} + \Delta C_{e\ gse} + \Delta C_{e\ eee} + \Delta C_{e\ fefe} \tag{3}$$

Moreover, the effects of each factor employing Eq. (3) can be estimated as follows:

$$\Delta C_{e_p} = w \times \ln\left(C_{e_{Pop}}^t \middle/ C_{e_P}^0 \right) \tag{4}$$

$$\Delta C_{e_{ae}} = w \times \ln\left(C_{e_{ae}}^t \middle/ C_{e_{ae}}^0 \right) \tag{5}$$

$$\Delta C_{e_{eie}} = w \times \ln\left(C_{e_{eie}}^t \middle/ C_{e_{eie}}^0 \right) \tag{6}$$

$$\Delta C_{e_{eoe}} = w \times \ln\left(C_{e_{eoe}}^t \middle/ C_{e_{eoe}}^0 \right) \tag{7}$$

$$\Delta C_{e_{gse}} = w \times \ln\left(C_{e_{gse}}^t \middle/ C_{e_{gse}}^0 \right) \tag{8}$$

$$\Delta C_{e_{eee}} = w \times \ln\left(C^t_{e_{eee}} \Big/ C^0_{e_{eee}} \right) \tag{9}$$

$$\Delta C_{e_{fefe}} = w \times \ln\left(C^t_{e_{fefe}} \Big/ C^0_{e_{fefe}} \right) \tag{10}$$

Where,

$$w = \ln\left(C^t_e - C^0_e \big/ \ln C^t_e - \ln C^0_e \right)$$

To check the linear error analysis, we used the vector error correction model. For this, the log-linear ARDL model by Pesaran et al. [66] is applied to investigate the relationship between carbon emissions and driving factors over the selected period in China due to the positive strength of this method, as provided in Eq. (11).

$$\ln C_{e_t} = \alpha_{0t} + \alpha_{1t}\ln p_t + \alpha_{2t}\ln ae_{it} + \alpha_{3t}\ln eie_t + \alpha_{4t}\ln eoe_t + \alpha_{5t}\ln gse_t + \alpha_{5t}\ln eee_t + \alpha_{5t}\ln fefe_t + \epsilon_t \tag{11}$$

Thus, the ARDL model involves the following unrestricted error model, as shown in Eq. (12).

$$\begin{aligned}\Delta \ln C_{e_t} = {} & \alpha_{0C_e} + \alpha_{iC_e}\sum_{i=1}^{n}\Delta\ln C_{et-1} + \alpha_{iP}\sum_{i=1}^{n}\Delta\ln p_{t-1} + \alpha_{iae_t}\sum_{i=1}^{n}\Delta\ln ae_{it-1} + \alpha_{ieie}\sum_{i=1}^{n}\Delta\ln eie_{t-1} + \alpha_{ieoe}\sum_{i=1}^{n}\Delta\ln eoe_{t-1} + \alpha_{igse}\sum_{i=1}^{n}\Delta\ln gse_{t-1} \\ & + \alpha_{ieee}\sum_{i=1}^{n}\Delta\ln eee_{t-1} + \alpha_{ifefe}\sum_{i=1}^{n}\Delta\ln fefe_{t-1} + \alpha_{1p}\ln C_{et-1} + \alpha_{2p}\ln p_{t-1} + \alpha_{3ae}\ln ae_{t-1} + \alpha_{4eie}\ln eie_{t-1} + \alpha_{5eoe_{it}}\ln eoe_{it-1} + \alpha_{6gse_{it}}\ln gse_{it-1} + \epsilon_t\end{aligned} \tag{12}$$

Where Δ is the difference operator, α is the intercept and Ɛ is the error.

3.3. Decoupling analysis

We estimated the decoupling states between CO_2 emissions and economic growth, and the decoupling index is measured as in Eq. (13). The Tapio decoupling model used in this research is the theoretical framework developed by Tapio [61], which separates the decoupling relationship between CO_2 emissions and economic growth into '8' states (Table 1). Compared with the model stated by the OECD, the decoupling model holds the advantages of low data requirements, accurate outcomes, and less calculation [67]. So, it has been widely used to analyze the relationship between ecological and environmental elements and economic growth (i.e., resource use) [68]. In this study, we introduce the Tapio decoupling model to study the relationship between CO_2 emissions and the economic growth of different sectors in China. The decoupling indexes can be calculated as in Eq. (13).

Table 1
Decoupling indicator measures [61].

No.	Categories	$\frac{\Delta C_e}{C_e}$	$\frac{\Delta G}{G}$	φ_t	Decoupling state
1	Negative decoupling	> 0	> 0	$D^t \geq 0$	Expansive negative decoupling
2		> 0	< 0	$D^t \leq 0$	Strong negative decoupling
3		< 0	< 0	$0.4 \geq D^t > 0$	Weak negative decoupling
4	Decoupling	< 0	> 0	$-0.4 > D^t \geq -1$	Weak decoupling
5		> 0	> 0	$-1 > D^t$	Strong decoupling
6		< 0	< 0	$D^t > 0$	Recessive decoupling
7	Coupling	< 0	> 0	$0 > D^t \geq -0.4$	Expansive coupling
8		< 0	< 0	$1 \geq D^t > 0.4$	Recessive coupling

$$\varphi^t(C_e, G) = \frac{\%\Delta C_e}{\%\Delta G} = \frac{\Delta C_e}{C_e} \Big/ \frac{\Delta G}{G} = \frac{\left(C^t_e - C^0_e\right)/C^0_e}{(G_t - G_0)/G_0} \tag{13}$$

where, $\varphi_t(C_e, G)$ indicates the decoupling elasticity of CO_2 emissions and GDP; $\%\Delta C_e$ indicates the percentage change in CO_2 emissions; $\%\Delta G$ shows the percentage change in gross domestic value; $C^t_e - C^0_e$ and $G_t - G_0$ indicates the CO_2 emissions and GDP at the final and initial periods, respectively. As per Tapio [61], the decoupling analysis is an elastic measure. Thus, based on the decoupling elasticity index, there are eight segmentations to show the status of decoupling, as shown in Table 1. Table 1 indicates that the decoupling state is the state where CO_2 emission pollution turns better. The negative decoupling state describes the worst CO_2 emissions pollution, while the coupling state states that CO_2 emissions and GDP rise or decline in the corresponding period at similar rates. Few scholars have employed decoupling analysis in different countries and regions; for example, Engo [69] for Cameroon's transport sector; Lin and Raza [70] for the electricity sector of Pakistan; Karmellos et al. [71] for the European Union-27 and the United Kingdom; and Song and Zhang [72] for different provinces in China. According to Tapio [61], the relationship between energy and economic growth from 0-t is validated as φ_t, as shown in Eqs. (12) and (13).

Referencing the previous studies' trend of growth, the decoupling associations between electricity and economic growth are evident at the maximum stage. But to date, we found only regional, individual sector, or provincial associations have been investigated in decomposition and decoupling analysis without taking all the electricity sectors of China. Hence, this study aims to contribute to the limited presenting literature in the current era by analyzing the relationship between different impacting factors in the decoupling elasticity index between CO_2 emissions and economic growth as follows in Eq. (14):

$$\varphi(C_e, G) = \frac{\frac{\Delta C_e}{C_{e0}}}{\frac{\Delta G}{G_0}} = \frac{\frac{\Delta C_{ep}}{C_{e0}}}{\frac{\Delta G}{G_0}} + \frac{\frac{\Delta C_{eae}}{C_{e0}}}{\frac{\Delta G}{G_0}} + \frac{\frac{\Delta C_{e_{eie}}}{C_{e0}}}{\frac{\Delta G}{G_0}} + \frac{\frac{\Delta C_{eeoe}}{C_{e0}}}{\frac{\Delta G}{G_0}} + \frac{\frac{\Delta C_{e_{gse}}}{C_{e0}}}{\frac{\Delta G}{G_0}} + \frac{\frac{\Delta C_{eeee}}{C_{e0}}}{\frac{\Delta G}{G_0}} + \frac{\frac{\Delta C_{e_{fefe}}}{C_{e0}}}{\frac{\Delta G}{G_0}} \tag{14}$$

$$= \varphi_{e_p} + \varphi_{ae} + \varphi_{eie} + \varphi_{eoe} + \varphi_{gse} + \varphi_{eee} + \varphi_{fefe} \tag{15}$$

where φ_t is the decoupling indicator. φ_{e_p}, φ_{ae}, φ_{eie}, φ_{eoe}, φ_{gse}, φ_{eee} , and φ_{fefe} indicates the decoupling indicators of population, activity, intensity, electricity overall effect, electricity generation, energy efficiency effect, and fuel emission factor effect. Under the measurement of sectorial decoupling, using Eq. (14) and (15), the individual decoupling can be estimated as follows in Eq. (16).

$$\varphi_t = \sum_{i}^{n} \varphi^t_{(\mathrm{ind,res,agr,com,tra,oth})} \tag{16}$$

Where, $\sum_i^n \varphi_t$ is the sum of all the sectors from i … n with individual decoupling indicators. φ_{ind}, φ_{res}, φ_{agr}, φ_{com}, φ_{tra}, and φ_{oth} denotes the decoupling between industrial, residential, agriculture, commercial, transport, and other sectors. In addition, to calculate the decoupling criteria, Tapio defined decoupling '8' states are used, as provided in Table 1.

4. Data sources

The study period for this research starts in 1990 and ends in 2020. In China, the data has been collected from different issues of the China Statistical Yearbook, the International Energy Agency (IEA) and the World Development Indicators. All the carbon emissions-related data have been collected from the BP Statistical Review of World Energy and the IEA and are in metric tons. The energy-related data, such as total electricity production, consumption, and the ratio of fuel generation, are measured in terawatt hours (TWh), while total electricity generation growth is considered in percentages. The annual data for real GDP, measured in billions of yuan of Chinese national currency, are taken from the China Statistical Yearbook [73]. Real GDP is calculated by dividing nominal GDP by a GDP deflator, i.e., $real\,GDP = no\min al\,\mathrm{GDP}/_{GDP\ deflator}$ and the population is in the million.

5. Empirical results

This section provides the major outcomes and their discussions based on decomposition analysis using key driving factors for carbon emissions, factor decoupling and sectoral decoupling analysis in China's electricity generation.

5.1. Analysis of CO_2 emissions from electricity generation and decomposition analysis in China

The subsequent CO_2 emissions from electricity generation in China have increased in total terms from 1991 to 2020. An aggregate CO_2 emission has risen from 2439.9 Mt CO_2 in 1991–9974.3 Mt CO_2 in 2020, following an annual growth rate of 3.09 %. Thus, it is evident from inputs that electricity generation and CO_2 emissions rose during the period; however, during 2019–2020, the CO_2 emissions from electricity generation were averagely dropped due to COVID-19. In addition, we derived decomposition equations to measure various driving factors linked to electricity generation, such as population, activity, intensity, electricity overall, generation structure, energy efficiency, and fuel emission factors. For this, we employed Eqs. (4)–(10) and show the results in Table 2 and Fig. 2, respectively. The objective of Table 2 and Fig. 2 is to estimate the effects of the decomposition of CO_2 emissions from electricity generation in China. For an easy understanding of the decomposition of variables, we derived all the outcomes in pictorial form, as shown in Fig. 2.

The decomposition outcomes during the 5-year planning period are presented in Table 2. Concerning policy implications, the study analyzes seven major economic plans for China's strategic policy measures. All the results of the decomposition analysis are presented for the periods 1991–1995, 1996–2000, 2001–2005, 2006–2010, 2011–2015, 2016–2020, and 1991–2020, respectively. The rise in CO_2 emissions is because of the obvious variations in population, activity and fuel emission factor's effects, followed by various sectors and economic growth. However, the change in activity effect ($\Delta C_{e_{ae}}$) is the key factor in increasing CO_2 emissions from electricity generation in China. It can be seen that from 1991 to 2020, the $\Delta C_{e_{ae}}$, ΔC_{e_p}, and $\Delta C_{e_{fefe}}$ were the major leading factors for rising CO_2 emissions from the electricity sector, which are in line with the studies [55,74]. Furthermore, the electricity efficiency effect ($\Delta C_{e_{eee}}$) was another factor in growing carbon emissions, which has a huge contribution in China, about 45 %. The electricity intensity effect ($\Delta C_{e_{eie}}$) looks to have a significant declining impact of 12.83, 16.90, 12.73, and 39.55 TWh/billion yuan during 1991–1995, 1996–2000, 2006–2010, and 2011–2015, respectively. The $\Delta C_{e_{eie}}$ found to be positive during 2001–2005 and 2016–2020 by 37.87 and 14.23 TWh/billion yuan, respectively. However, the mitigation of CO_2 emissions is about the obvious enhancements in electricity generation productivity and subsequently, the electricity intensity and sectoral share. In addition, the $\Delta C_{e_{eie}}$ is the most imperative factor in the rise in CO_2 emissions from electricity generation in China. The $\Delta C_{e_{eie}}$ outcomes show that CO_2 emissions decreased in most years, excluding 2001–2005. The aggregated impact is a decrease of 33.37 TWh/billion yuan, which adds to 2.60 % of the overall variations in CO_2 emissions in absolute value. These results are consistent with the study by Zhang et al. [75] on China's electricity intensity. The current period shows varied results due to the COVID-19 epidemic situation in China. The overall variations of China's $\Delta C_{e_{eie}}$ for the periods 1991–2000 and 2006–2020, as shown in Table 3, present a continuous decline, which may be due to new technologies, infrastructure and extensive application of advanced management and energy-saving technologies. Over the period 2011–2015, the $\Delta C_{e_{eie}}$ effect of absolute value is much larger than that in other planning periods, which might be attributed to the relative values of other effects in 1991–2010 and 2016–2020. Overall, the $\Delta C_{e_{eie}}$ added 33.37 TWh/billion yuan during 1991–2020, shows that the overall outcomes show that total electricity consumption was reduced and economic growth was increased, which is clear from the activity and population effects.

The population effect (ΔC_{e_p}) presents a significant rising effect in China because of the growing electricity demand, which is consistent with Karmellos et al. [71] and Song et al. [76]. The electricity overall effect ($\Delta C_{e_{eoe}}$) increases the CO_2 emissions in China because of energy import and export. As shown in Table 2, the $\Delta C_{e_{eoe}}$ provide negative values occurred during 1996–2000, 2001–2005, 2006–2010, 2011–2015, and 2016–2020, indicating a huge import of electricity-related fuels, while 1991–1995 shows that China has exported some kind of energy to other countries. For instance, China exported crude oil and coal at maximum levels of 7, 63,128 and 10, 25,411 TJ during 1991–1995 [4], which is beneficial to saving foreign reserves. Moreover, the $\Delta C_{e_{eie}}$ and $\Delta C_{e_{gse}}$ factors played a significant role in lessening CO_2 emissions during the studied period. It is clearly stated that the generated electricity is at its maximum due to modern and updated energy structures. The percentage change in electricity generation significantly increased by 41 % during 1991–2020. Our outcomes also present that thermal electricity plays a minor role in rising carbon emissions and acts as a third major role in electricity generation, as shown in Fig. 1. The accumulated effect of $\Delta C_{e_{gse}}$ is reduced by 1087.041 %/TWh, which adds 19.6 % of the total electricity generation structure in absolute value, which presents that the substitution of hydro, solar, nuclear, and wind had a significant impact on reducing CO_2 emissions. As per Song et al. [76], the use of electricity can substitute coal and fossil fuels with clean energy, which is known as inside electric substitution based on the modern infrastructure of clean energy. The $\Delta C_{e_{eee}}$ effect

Table 2
Driving factors' decomposition of CO_2 emissions from China's electricity generation during 1991–2020.

Period	ΔC_{e_p}	$\Delta C_{e_{ae}}$	$\Delta C_{e_{eie}}$	$\Delta C_{e_{eoe}}$	$\Delta C_{e_{gse}}$	$\Delta C_{e_{eee}}$	$\Delta C_{e_{fefe}}$	$\Delta C_{e_{total}}$
1991–1995	5.623	54.320	−12.830	1.415	−55.449	52.183	49.896	95.159
1996–2000	6.623	51.509	−16.900	−0.060	7.386	−5.184	30.272	73.647
2001–2005	6.621	96.995	37.877	−1.359	−37.541	43.641	121.571	267.805
2006–2010	8.916	175.195	−12.727	−1.484	−211.164	192.331	111.371	262.437
2011–2015	15.156	156.885	−39.551	−7.957	−2311.682	2247.860	44.983	105.693
2016–2020	11.540	135.757	14.238	3.163	−439.338	395.380	138.944	259.685
1991–2020	66.358	768.852	−33.366	−7.642	−1087.041	1021.206	660.003	1388.369

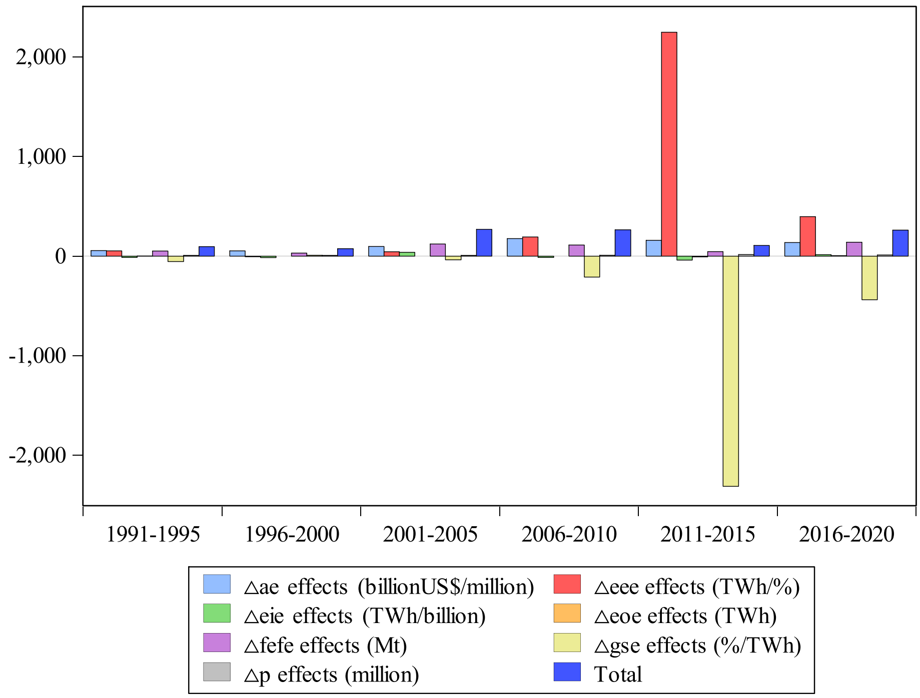

Fig. 2. Decomposition variations in electricity consumption factors from 1991 to 2020.

showed positive contributions in all the intervals excluding 1996–2000, which declined by 0.09 % due to the energy crisis. Overall, the positive results show that the percentage of electricity generation is increasing, which is proof of the new energy generation framework. Therefore, the technological improvements aim to enhance efficiency to reach the 2060 goals. In general, the $\Delta C_{e_{eee}}$ effects are quite exciting because this factor leads to a reduction in CO_2 emissions. There have been changes in the proportion of fuel, such as fossil fuels, to renewable energy since 2000, which were the key factors activating the variations. Consequently, these measures of renewable energy policies can lead China to mitigate CO_2 emissions. To clearly understand the yearly variation in the entire factor's decomposition, the outcomes are presented in Appendix A.

Finally, the fuel emission factor effect ($\Delta C_{e_{fefe}}$) reveals that all the statistics are positive but moving with a declining trend. For example, during the second, fourth and fifth intervals, the $\Delta C_{e_{fefe}}$ declined by 0.60 %, 0.91 % and 0.40 %, which are still showing the maximum values. In addition, the increase in energy demand can raise CO_2 emissions [10]. If there is an enhancement in energy structure and efficiency or renewable energy substitution, then pollution emissions can be controlled. Therefore, in the future, it is essential and a breakthrough for CO_2 emissions to set the share of renewable energy in electricity. Based on the LMDI method, the current study measures the major factors that affect CO_2 emissions from China's electricity consumption. However, this study found that the activity effect ($\Delta C_{e_{ae}}$) is the only factor that is increasing CO_2 emissions, while the energy efficiency effect ($\Delta C_{e_{eee}}$) is the factor that is declining CO_2 emissions. In addition, to mitigate the CO_2 emissions from China's electricity generation, much concentration is needed on the affecting factors with a lower effect. The linear outcomes under econometric analysis in Eqs. (11) and (12), Table A provided in supplementary data presents the variable coefficients, t-ratio, p-values, R-square, adjusted R-square, ECM, and model's stability tests (i.e., cumulative sum and cumulative sum of squares) when CO_2 is the dependent variable. The calculated long-run coefficients show that all the variables significantly impact carbon emissions. The coefficients of population, activity, energy efficiency, and fuel emission effects are positive and significant, which are in line with the decomposition analysis. The ECM term [−0.4494] is significant with an estimated sign and gives long-term convergence to the long-term equilibrium. Consequently, the CUSUM and CUSUM-square show that our supposed model is stable (see results in supplementary data Figs. A1-A2). To check the individual effect of each factor and sector respecting intensity analysis, we employed the decoupling index [61], which not only explains the degree of decoupling but also measures the reasons for decoupling states. It not only links the degree of decoupling in different regions or provinces but also decouples the industry, sector and country [55]. Declining returns can lessen the motivation to invest in new technologies, infrastructure and new power plants for electricity generation. Higher efficiency can improve productivity, enhance income gaps among sectors, enhance return on investment, and motivate investors to raise their investment in new production technologies. To enhance such factors, it is necessary to decouple individual factors and sectors, which are discussed below.

5.2. Decoupling state estimation

Based on Eqs. (13)–(16), we analyzed the decoupling states, individual factors, and sectoral decoupling during 1991–2020. As per the decomposition analysis, we found that the $\Delta C_{e_{ae}}$ effect is the key driving factor of huge electricity use. Thus, the decoupling states of CO_2 emissions and economic growth were estimated using Tapio's method, and the outcomes are shown in Table 3. From Table 3, we found two decoupling states of GDP and CO_2 emissions in China during the study period: expansive negative decoupling and expansive coupling, respectively. This shows that the economic development ratio is faster in the long-run than that of CO_2 emissions. The expansive negative decoupling was found in the maximum periods of 1991–1997, 1998–2015 and 2016–2020. The expansive coupling was found in 1997–98 and 2015–16, respectively.

It can be seen that the expansive negative decoupling shows that economic growth grows and CO_2 emissions increase at a maximum level. This shows that the overall production scale increased faster, increasing fuel demand and raising economic growth, which is consistent with the studies of Zhang et al. [5] and Song et al. [76]. They employed decoupling analysis and proved that electricity consumption and GDP are the major factors in growing CO_2 emissions in China. In addition, these may occur due to the industrial revolution, fuel substitution, and the

Table 3
Estimation of decoupling state of electricity carbon emissions and economic growth in China.

Year	$\%\Delta C_e$	$\%\Delta G$	φ_t	Decoupling states	Score
1991–1992	0.0817	0.1422	0.5744	Expansive Negative Decoupling	I
1992–1993	0.1615	0.1586	1.0182	Expansive Negative Decoupling	I
1993–1994	0.0875	0.1696	0.5162	Expansive Negative Decoupling	I
1994–1995	0.1498	0.1611	0.9301	Expansive Negative Decoupling	I
1995–1996	0.2218	0.1619	1.3700	Expansive Negative Decoupling	I
1996–1997	−0.0350	0.1656	−0.2114	Expansive Coupling	II
1997–1998	0.0856	0.1537	0.5569	Expansive Negative Decoupling	I
1998–1999	0.0564	0.1619	0.3486	Expansive Negative Decoupling	I
1999–2000	0.1362	0.1931	0.7052	Expansive Negative Decoupling	I
2000–2001	0.1226	0.2057	0.5959	Expansive Negative Decoupling	I
2001–2002	0.2918	0.2442	1.1951	Expansive Negative Decoupling	I
2002–2003	0.4319	0.2929	1.4747	Expansive Negative Decoupling	I
2003–2004	0.3132	0.3247	0.9647	Expansive Negative Decoupling	I
2004–2005	0.2860	0.4028	0.7100	Expansive Negative Decoupling	I
2005–2006	0.4767	0.5009	0.9515	Expansive Negative Decoupling	I
2006–2007	0.3696	0.6317	0.5852	Expansive Negative Decoupling	I
2007–2008	0.0564	0.4893	0.1153	Expansive Negative Decoupling	I
2008–2009	0.2782	0.5226	0.5324	Expansive Negative Decoupling	I
2009–2010	0.4611	0.6469	0.7127	Expansive Negative Decoupling	I
2010–2011	0.7140	0.6427	1.1109	Expansive Negative Decoupling	I
2011–2012	0.1479	0.5797	0.2551	Expansive Negative Decoupling	I
2012–2013	0.4008	0.6176	0.6490	Expansive Negative Decoupling	I
2013–2014	0.0428	0.6363	0.0673	Expansive Negative Decoupling	I
2014–2015	−0.2237	0.6482	−0.3452	Expansive Coupling	II
2015–2016	0.1829	0.6749	0.2710	Expansive Negative Decoupling	I
2016–2017	0.4319	0.7315	0.5905	Expansive Negative Decoupling	I
2017–2018	0.4981	0.7600	0.6553	Expansive Negative Decoupling	I
2018–2019	0.2121	0.7224	0.2935	Expansive Negative Decoupling	I
2019–2020	0.1595	0.2803	0.5691	Expansive Negative Decoupling	I

dependence on indigenous energy resources, i.e., coal, gas and renewable energy resources. In the expansive coupling state, the real GDP increases while CO_2 emissions reduce at a minimum level, where the elasticity values decrease at a rate of 0.211 and 0.345. This coincidence shows a close association between real GDP and CO_2 emissions; thus, it is clear that China practiced developments associated with energy-related sectors, industries and taxes. The findings show that local governments should formulate effective policies to attain energy conservation and low-carbon for huge emitting sectors and are consistent with [77]. Overall, the decoupling trend in China relies on an expansive negative decoupling state. Finally, it can be concluded that coal and clean energy added 56.8 % and 15.9 % of gross energy production in 2020, respectively, indicating that coal remains China's most reliable energy source [73]. Many countries around the world are starting to concentrate on the energy transition; for example, Chapman and Okushima [78] for Japan, Raza and Lin [79] for Pakistan, and Loewen [80] for the European Union. In respect of international pressure and energy transformation, China illuminated the strategic goal of the energy revolution. For this, on September 22, 2020, President Xi announced that China would make an effort to peak CO_2 emissions by 2030 and be carbon-neutral by 2060. This shows that all the states present relevant outcomes, which will help policymakers, attempt their efforts for China's future. Furthermore, the indexes of individual factors are also investigated for future perspectives, which are provided in Fig. 3.

5.3. Sectorial decoupling indexes of electricity consumption and value-added (unit:%), 1991–2020

Given the six major productive sectors, including agriculture, commercial, industrial, transport, residential, and others, during 1991–2020, we can see that these sectors raised the relative weight on electricity consumption by 0.27, 2.58, 0.47, 3.54, 3.55, and 5.40 %, respectively. Also, it can be noted that during 2019–2020, the transport and residential sectors were the only sectors that grew by 7.68 and 15.40 %, while the industrial sector remained lower by 0.28 % due to COVID-19. Moreover, the economic situation has decreased because of the lockdown situation in the country, especially the shutdown of the industrial and commercial sectors. This change permits us to regulate the electricity use of China as a whole and at sectorial levels, as shown in Fig. 4 and Appendix B. All the decomposition outcomes are taken from Eq. (16). Based on Tapio's theory, economic growth has shifted strongly, and the reliance on CO_2 emissions is gradually declining in various sectors. These are the reasons for the provincial and sectorial enhancements. For example, the state of expansive negative decoupling during the 12th five-year energy and economic planning period of China implies that each province should increase its efforts to apply energy-saving and CO_2 reduction policies, adjust its industrial structure, and develop advanced emission-reduction technologies [77]. The region can therefore attain the decoupling state of industrial, transport, agriculture, residential, and commercial sectors in terms of CO_2 emissions and economic growth and make more contributions to the whole of China. The residential building CO_2 emissions grew faster than the per capita income in the current period due to numerous construction projects to meet the residential demand, which is in line with Huo et al. [77]. This certainly raised the energy consumption and CO_2 emissions of the residential sector. Moreover, to enhance the economic and sectoral situation, China has comprehended the adoption of different policies aiming for energy efficiency improvements in productive sectors over the defined and future period of China's energy vision-2060. Therefore, the CO_2 emissions in China could be lessened by energy-intensive industries; however, energy efficiency and energy-saving are targets, but they still contribute to the CO_2 emissions in the individual sector, which could be declined by employing different domestic energy resources, i.e., wind, biomass, hydro, solar, and clean coal [81]. Policy implications for productive sectors generally include regulatory estimations at the country level, for instance, voluntary agreements, financial incentives, monetary policies, and technological advancements. Besides, energy intensity and economic effects have also become factors in growing energy consumption during the stated period (1991–2020). In general, when these productive sectors are analyzed, each sector's intensity should be less energy-intensive. As shown in Fig. 4, each sector has a long volatility and decoupling relationship between them, which shows a 30-year threshold in Appendix B.

6. Discussion

The electricity sector plays an imperative role in meeting the environmental goals of China, involving CO_2 emissions mitigation and carbon neutrality. Rises in renewable energy generation, coupled with

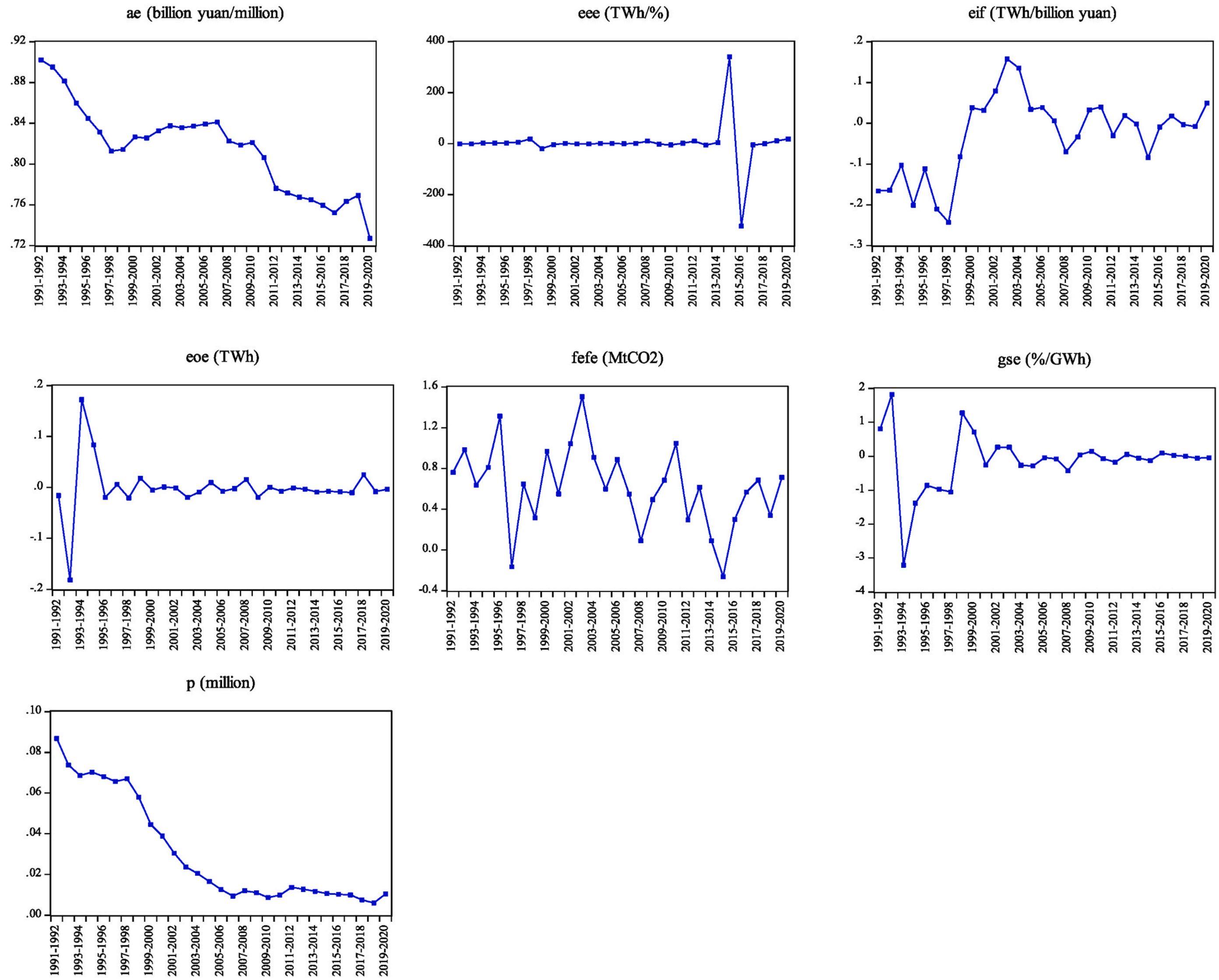

Fig. 3. Decoupling of sub-indicators for CO_2 emissions from electricity generation in China from 1991 to 2020.

electrification in various sectors, can generate significant mitigations in carbon emissions [60]. Several current modeling studies have estimated deep carbonization scenarios for China's energy system, with importance in 2050, whose objective was to attain 1.5 and 2 °C scenarios for China, involving the power sector, out to 2050 [e.g., 82,83]. In this section, research on similar subjects, limited to factors, as well as research that was done in different areas, such as a whole, sectorial, or regional perspective (section 2), is used to compare these other research findings with the study's outcomes. As can be seen from the research findings above, the current study findings are partly consistent with other research on similar topics. The differences are caused by the heterogeneity that occurs in the research samples, period, factors, framework, and methods used in these studies. This particular research comprises the following new features compared with others; however, related studies concentrated on climate change or CO_2 emissions when discussing regional or total impact. However, this study reflects electricity generation, CO_2 emissions, leading factors, sectorial electricity consumption, and economic development using decomposition and decoupling approaches in China to analyze the comprehensive environmental impacts. Moreover, this study also enriches the analytical framework for environmental impact decomposition analysis based on various factors and estimates decoupling efforts from different viewpoints (factors and sectorial). In the field of global climate change and China's carbon neutrality goal, it is necessary to calculate the effect of the individual sector's performance. Though the study found that the activity effect is the only factor that is growing CO_2 emissions, energy efficiency is the factor that is declining emissions over the period. To reduce CO_2 emissions from the various sectors, the country should concentrate on the energy substitutability of the various sectors.

Last but not least, the findings are conductive to give decision support for local policy makers to develop effective CO_2 emissions reduction measures for short- and long-term carbon peak and carbon neutrality at the sectoral levels. Based on impacting factors, multiple decoupling states are described in Table 3 and Fig. 4, which show that the economic growth ratio is faster than that of CO_2 emissions. It has the advantages of identifying the major driving factors that have encouraging and balancing effects on sectorial CO_2 emissions and enlightening the differential decoupling associations. Also, it can be used in more regions facing similar issues to validate the effectiveness of the model framework and provide more suitable and scientific management planning for attaining carbon neutrality and carbon peak. Thus, Tapio's index based on '8' states (Figs. 3 and 4) gives a significant rising trend with varied carbon emissions effects over the period, which shows that the indexes of each factor will help the policymakers efforts for China's development. Moreover, the sectorial variations in the '6' major sectors provide productive results during the studied period, which shows that all the

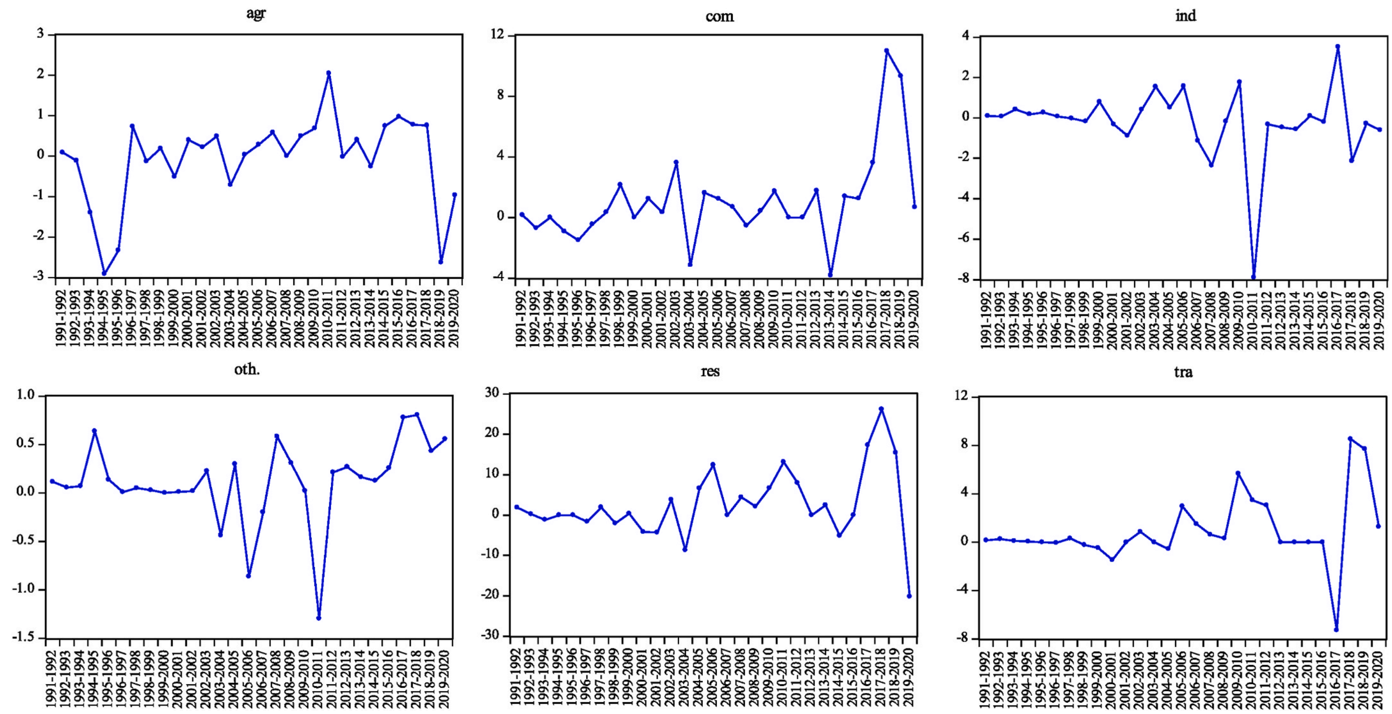

Fig. 4. Decoupling index of sectorial electricity and value added (% change), 1991–2020.

sectors have rising returns between zero to 26 % growth, respectively. All the findings are more detailed and comprehensive, and suggestions are more useful to the context as well as the decoupling effort trends of countries, regions and sectors that can be carried-out for decoupling efforts. Thus, in the acceleration process of electrification and decarbonization, it is necessary to discover the industrial restructuring that brought about the changeability in the electricity price and technology, resulting in less consumption in the general business and heavy pollution industries [82]. Moreover, the econometric outcomes present significant results that will have long-term policy implications and help policymakers understand the situation under the driving factors.

7. Conclusion and policy suggestions

As the largest energy consumer and carbon emitter country in the world, China's CO_2 emissions mitigation in electricity generation is a serious step toward confronting the challenges of climate change and a low-carbon economy. This study tried to find the electricity-related CO_2 emissions in China and productive sectors using seven key driving factors. The objective was to check the factor's relationship and get the reduction direction of CO_2 emissions in the electricity sector from 1991 to 2020. Thus, this study employs an LMDI method to decompose the CO_2 emissions variations in China's electricity generation and Tapio's decoupling method to see the decoupling states among the factors. Based on empirical analysis, the major results show that:

First, decomposition analysis is divided into a 5-year economic plan and then investigated annually using activity, population, electricity intensity, electricity overall, generation structure, energy efficiency, and fuel emission factor effects. The outcomes prove that population, economic activity, and fuel emission factor effects are the leading factors in growing CO_2 emissions. The electricity intensity effect and generation structure effect show significant contributions to mitigating CO_2 emissions at maximum intervals. All the outcomes are supported by the literature and are mainly counterbalanced by the proportion of the electricity generation effect.

Second, the decoupling state in China from 1991 to 2020 has changed significantly and can be seen in two phases: expansive negative decoupling and expansive coupling, which provide progressive outcomes. The results show that economic growth is growing quickly, which causes carbon emissions. It can be seen that the expansive negative decoupling shows that economic growth grows and CO_2 emissions increase at a maximum level. This shows that the overall production scale increased faster, growing the fuel demand and raising economic growth. During the investigated period, China's CO_2 emissions and economic growth gradually increased due to its dependence on huge energy consumption.

Third, regarding the decomposition outcomes for the decoupling between sectorial levels, the changing intensity shows a major effect (i.e., expansive negative decoupling), while most of the sectors have a primarily promoting effect. However, economic and energy demand also have a driving effect on the decoupling change between each indicator. However, weak decoupling in the future can occur due to renewable energy technologies, clean coal technologies and electricity generation infrastructure in China.

Fourth, regarding electricity generation and CO_2 emissions in China, policy suggestions for CO_2 emissions reduction can be proposed as follows: (1) Seeing to the future, the largest scope for lessening CO_2 emissions from power generation looks to be from variations in the fuel mix, especially moving away from coal. This is because coal is the key energy type in China, which accounts for 70 % of the primary energy supply. Thus, implementing clean coal technologies and promoting indigenous consumption of coal briquettes may be the most efficient pathways for lessening CO_2 emissions. CO_2 emissions-related policies were planned by the Chinese government during the 12th, 13th and 14th Five-Year Plan periods, and the situation remained unbalanced. The renewable energy development should advocate green development and frame the maximum CO_2 emission plan, and renewable energy (i.e., hydro, wind, solar, etc.) has the largest word frequency, which will restructure clean energy policy to some degree. Thus, goal-setting should depend on an analysis of the factors impacting the variation in CO_2 emissions within specific regions. Various low-performing power grids, especially in highly populated and industrialized cities, permit tailored policies for CO_2 emissions management. (2) In our case, policymakers should contribute to the implications of sectorial policies based on a new factor's understanding in our decoupling research. Our empirical results show unfavorable changes in China's decoupling index, which is mainly caused by the expansion of activity, population effect, production, and international trade. Policymakers need to reconsider before releasing economic incentive bundles, particularly in considered sectors. The policymakers should give preference to enhancing energy-saving technologies, energy management level, and supply sectors. (3) The decision-making process should be based on theoretically sound methodologies, for example, the application of decomposition and decoupling methods to estimate the driving factors and their indexes on change in CO_2 emissions, which are expected to play their dual roles. Moreover, energy efficiency and energy mixed effects can be strengthened by fuel substitution, privatization, taxes, professional talents, and enhancing production capacity, while generation efficiency can be enhanced through market-based mechanisms besides command-and-control regulations. It is also necessary to set the formation of a carbon trading market system focusing on CO_2 emissions from electricity generation, thus introducing a market mechanism to regulate emission reduction quotas in which highly economically developed regions should be given more responsibility.

7.1. Study limitation

The current research highlights the important limitations of China's electricity efficiency and carbon mitigation potential goals. We found a few limitations in the study that can be resolved in the future, such as the data limitations of each variable that can be estimated for the coming economic plan (2021–2025). Further study can be made on the causality analysis and then check the intensity changes over time. In addition, future studies can also be done using energy cost, sectorial, and regional causality analysis to check the individual causation for each sector and region. Also, as discussed above, the current measures are based on various substituting factors to check the country's electricity CO_2 emissions and economic situation; however, electricity efficiency and technological coefficients can be further analyzed based on the availability of data.

CRediT authorship contribution statement

Linying Li: Data collection, Methodology, Formal analysis, Interpretation, and critical revision of the article. **Muhammad Yousaf Raza:** Research concept, Methodology, Software, Data collection, Interpretation, Formal analysis, critical revision of the article. **Marco Cucculelli:** Methodology, Software, Data collection, Interpretation, Formal analysis, and critical revision of the article.

Declaration of competing interest

We declare that there is no conflict of interest.

Data availability

Data will be made available on request.

Appendix A

Various driving factors' decomposition and CO_2 emissions from electricity generation of China from 1991 to 2020.

Period	$\Delta C_{e_p \text{ effects}}$	$\Delta C_{e_{ae} \text{ effects}}$	$\Delta C_{e_{eie} \text{ effects}}$	$\Delta C_{e_{eoe} \text{ effects}}$	$\Delta C_{e_{gse} \text{ effects}}$	$\Delta C_{e_{eee} \text{ effects}}$	$\Delta C_{e_{fefe} \text{ effects}}$	$\Delta C_{e_{total}}$
1991–1992	1.2750	12.5609	−2.4887	−0.2335	11.4122	−10.0851	10.6887	23.1295
1992–1993	1.3342	13.7542	−3.1393	−3.3977	26.6199	−28.8632	15.3169	21.6251
1993–1994	1.4540	14.3108	−2.3688	3.8196	−63.2209	61.9772	10.5226	26.4945
1994–1995	1.5258	13.0713	−4.9689	1.8793	−42.1891	40.7254	12.7702	22.8140
1995–1996	1.6654	13.3662	−3.2238	−0.5002	−39.5386	42.9019	21.0454	35.7163
1996–1997	1.7243	13.1602	−6.7905	0.1519	−66.3434	66.4979	−2.6986	5.7018
1997–1998	1.6406	11.2738	−7.7130	−0.5305	−113.4097	114.0216	9.7935	15.0763
1998–1999	1.5421	11.6057	−2.9533	0.5111	140.1965	−137.6280	5.0203	18.2943
1999–2000	1.4787	13.8135	1.7276	−0.1871	58.2617	−59.5425	18.1598	33.7116
2000–2001	1.4573	14.6052	1.6175	0.0426	−22.0371	16.4281	10.9179	23.0315
2001–2002	1.4812	17.8418	5.2115	−0.0802	28.6901	−25.9368	24.8853	52.0929
2002–2003	1.6006	22.9813	13.9380	−1.4610	35.2178	−29.4594	43.3857	86.2031
2003–2004	1.7495	26.6298	14.4434	−0.8303	−45.8180	41.4843	29.1572	66.8158
2004–2005	1.9090	33.1176	4.7841	1.2292	−81.6673	82.5283	24.0372	65.9381
2005–2006	2.0236	41.3739	7.3981	−1.3524	−21.0546	24.5598	44.8838	97.8322
2006–2007	2.1151	51.7670	1.5461	−0.5565	−57.6550	59.3713	35.2648	91.8528
2007–2008	2.1856	37.1123	−15.5761	3.2507	−432.7847	412.5963	4.5172	11.3012
2008–2009	2.2041	37.6030	−8.4901	−4.4032	78.2564	−71.5214	26.4127	60.0615
2009–2010	2.3176	46.1862	11.0824	0.1607	241.4613	−248.5009	45.3116	98.0190
2010–2011	2.9411	46.1544	14.6725	−2.6582	−116.4696	128.7010	69.0440	142.3853
2011–2012	3.9484	40.1134	−10.7997	−0.3073	−456.1481	431.9261	17.5020	26.2350
2012–2013	4.0585	41.5142	7.6349	−1.2363	208.9327	−210.4003	39.0626	89.5663
2013–2014	3.9818	41.2674	−0.7407	−3.6613	−220.2173	200.3693	5.8859	26.8852
2014–2015	3.6201	38.7445	−37.0516	−3.1553	−1935.9982	1915.9496	−17.2003	−35.0912
2015–2016	3.5562	37.5535	−4.3982	−3.6081	1771.9839	−1785.9507	20.5258	39.6623
2016–2017	3.9409	39.7918	9.5320	−5.0601	170.8802	−177.3754	42.1479	83.8574
2017–2018	3.2623	42.3007	−2.1101	13.4843	12.0140	−18.6498	52.6849	102.9863
2018–2019	2.6014	40.1981	−4.6921	−4.3794	−468.2195	450.1845	24.6810	40.3739
2019–2020	1.7899	14.5730	11.5312	−0.7682	−207.0068	192.4449	20.0292	32.5931
1991–2020	66.3583	768.8516	−33.3661	−7.6423	−1087.0407	1021.2055	660.0029	1388.3692

Appendix B

Decoupling indexes of sectorial change from 1991 to 2020 (unit: % change).

Year	φ_{ind}	φ_{res}	φ_{agr}	φ_{com}	φ_{tra}	φ_{oth}
1991–1992	0.0972	1.8355	0.0888	0.1626	0.1612	0.1153
1992–1993	0.0646	0.2151	−0.1110	−0.6885	0.2594	0.0582
1993–1994	0.4124	−1.1509	−1.3953	0.0000	0.1139	0.0713
1994–1995	0.1762	0.0000	−2.9172	−0.9113	0.0536	0.6377
1995–1996	0.2746	0.0000	−2.3284	−1.5034	0.0000	0.1377
1996–1997	0.0732	−1.6402	0.7295	−0.4493	−0.0483	0.0090
1997–1998	−0.0209	1.8967	−0.1309	0.3463	0.3169	0.0526
1998–1999	−0.1775	−2.0772	0.1886	2.1576	−0.2313	0.0300
1999–2000	0.7889	0.3832	−0.5120	0.0000	−0.4746	0.0019
2000–2001	−0.3172	−4.1809	0.3974	1.2474	−1.4687	0.0122
2001–2002	−0.8860	−4.3114	0.2236	0.3364	0.0000	0.0202
2002–2003	0.4004	3.8096	0.4891	3.6168	0.8724	0.2273
2003–2004	1.5501	−8.6779	−0.7101	−3.1474	0.0000	−0.4401
2004–2005	0.5133	6.6499	0.0350	1.6406	−0.5754	0.3019
2005–2006	1.5803	12.4080	0.2854	1.2361	2.9704	−0.8617
2006–2007	−1.1420	0.0000	0.5844	0.7036	1.4900	−0.1982
2007–2008	−2.3434	4.4312	0.0000	−0.5406	0.6165	0.5835
2008–2009	−0.1746	2.1092	0.4957	0.4316	0.3177	0.3096
2009–2010	1.7669	6.7113	0.6863	1.7369	5.6707	0.0228
2010–2011	−7.9020	13.1699	2.0490	0.0000	3.4655	−1.2961
2011–2012	−0.3152	7.9602	−0.0186	0.0000	3.0402	0.2138
2012–2013	−0.4665	0.0000	0.4024	1.7731	0.0000	0.2703
2013–2014	−0.5591	2.4847	−0.2529	−3.8354	0.0000	0.1626
2014–2015	0.0948	−5.1718	0.7440	1.4107	0.0000	0.1281
2015–2016	−0.1965	0.0000	0.9769	1.2520	0.0000	0.2573
2016–2017	3.5135	17.3045	0.7804	3.6267	−7.2795	0.7799
2017–2018	−2.1339	26.2100	0.7587	10.9861	8.5052	0.8046
2018–2019	−0.2835	15.4089	−2.6356	9.3399	7.6890	0.4335
2019–2020	−0.6043	−20.1834	−0.9669	0.6847	1.2708	0.5552

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esr.2024.101304.

References

[1] M.Y. Raza, B. Lin, Analysis of Pakistan's electricity generation and CO2 emissions: based on decomposition and decoupling approach, J. Clean. Prod. 359 (2022) 132074.
[2] IEA. https://www.iea.org/data-and-statistics/data-tools/energy-statistics-data-browser?country=WORLD&fuel=Energy%20consumption&indicator=TotElecCons, 2021.
[3] P. Fragkos, N. Kouvaritakis, Model-based analysis of intended nationally determined contributions and 2 C pathways for major economies, Energy 160 (2018) 965–978.
[4] IEA. https://www.iea.org/data-and-statistics/data-tools/energy-statistics-data-browser?country=CHINA&fuel=CO2%20emissions&indicator=CO2BySector, 2021.
[5] C. Zhang, B. Su, K. Zhou, S. Yang, Analysis of electricity consumption in China (1990–2016) using index decomposition and decoupling approach, J. Clean. Prod. 209 (2019) 224–235.
[6] H. Gohli, High-voltage steering: China's energy market reforms, industrial policy tools and the 2021 electricity crisis, Energy Res. Social Sci. 93 (2022) 102851.
[7] K.L. O'Brien, R.M. Leichenko, Double exposure: assessing the impacts of climate change within the context of economic globalization, Global Environ. Change 10 (3) (2000) 221–232.
[8] Y.J. Ding, C.Y. Li, W.A.N.G. Xiaoming, Y. Wang, S.X. Wang, Y.P. Chang, Z.R. Wang, An overview of climate change impacts on the society in China, Adv. Clim. Change Res. 12 (2) (2021) 210–223.
[9] D. Samaniego-Rascón, M.C.G. da Silva, A.D. Ferreira, R.E. Cabanillas-Lopez, Solar energy industry workers under climate change: a risk assessment of the level of heat stress experienced by a worker based on measured data, Saf. Sci. 118 (2019) 33–47.
[10] H. Mei, Y.P. Li, C. Suo, Y. Ma, J. Lv, Analyzing the impact of climate change on energy-economy-carbon nexus system in China, Appl. Energy 262 (2020) 114568.
[11] S. Lu, X. Bai, X. Zhang, W. Li, Y. Tang, The impact of climate change on the sustainable development of regional economy, J. Clean. Prod. 233 (2019) 1387–1395.
[12] Y. Wang, J. Huang, Pathway to develop a low-carbon economy through energy-substitution technology in China, Energy 261 (2022) 124964.
[13] Yu Ma, A Study on the Estimation of the Desirable Range of Cross-Border Capital Flows in Emerging Economies[M], China Social Sciences Press, Beijing, 2023.
[14] World Energy Outlook, 2018. https://www.iea.org/reports/world-energy-outlook-2018.
[15] P. Xie, S. Gao, F. Sun, An analysis of the decoupling relationship between CO2 emission in power industry and GDP in China based on LMDI method, J. Clean. Prod. 211 (2019) 598–606.
[16] J. Wu, Q. Guo, J. Yuan, J. Lin, L. Xiao, D. Yang, An integrated approach for allocating carbon emission quotas in China's emissions trading system, Resour. Conserv. Recycl. 143 (2019) 291–298.
[17] Q. Yan, Y. Wang, T. Baležentis, D. Streimikiene, Analysis of China's regional thermal electricity generation and CO2 emissions: decomposition based on the generalized Divisia index, Sci. Total Environ. 682 (2019) 737–755.
[18] G. Wu, Z. Miao, S. Shao, Y. Geng, J. Sheng, D. Li, The elasticity of the potential of emission reduction to energy saving: definition, measurement, and evidence from China, Ecol. Indicat. 78 (2017) 395–404.
[19] B. Lin, R. Zhu, M.Y. Raza, Fuel substitution and environmental sustainability in India: perspectives of technical progress, Energy 261 (2022) 125309.
[20] M.L. Song, R. Fisher, J.L. Wang, L.B. Cui, Environmental performance evaluation with big data: theories and methods, Ann. Oper. Res. 270 (1) (2018) 459–472.
[21] J. Feng, L. Zhao, H. Jia, S. Shao, Silk Road Economic Belt strategy and industrial total-factor productivity: evidence from Chinese industries, Manag. Environ. Qual. Int. J. (2018).
[22] Y. Qu, J. Li, S. Wang, Green total factor productivity measurement of industrial enterprises in Zhejiang Province, China: a DEA model with undesirable output approach, Energy Rep. 8 (2022) 307–317.
[23] Y. Li, H. Xue, L. Lin, F. Li, L. Liang, G. Kou, Provincial production and pollution treatment performance in China based on a two-stage eco-inefficiency approach with undesirable intermediate outputs, J. Clean. Prod. 331 (2022) 130016.
[24] J. Wang, S. Zhang, Q. Zhang, The relationship of renewable energy consumption to financial development and economic growth in China, Renew. Energy 170 (2021) 897–904.
[25] Z. Jia, B. Lin, CEEEA2. 0 model: a dynamic CGE model for energy-environment-economy analysis with available data and code, Energy Econ. 112 (2022) 106117.

[26] X. Zhao, M. Mahendru, X. Ma, A. Rao, Y. Shang, Impacts of environmental regulations on green economic growth in China: new guidelines regarding renewable energy and energy efficiency, Renew. Energy 187 (2022) 728–742.
[27] IEA. https://www.iea.org/policies/6277-china-13th-renewable-energy-development-five-year-plan-2016-2020, 2020.
[28] X. Zhao, Q. Ma, R. Yang, Factors influencing CO2 emissions in China's power industry: Co-integration analysis, Energy Pol. 57 (2013) 89–98.
[29] B. Gong, X. Zheng, Q. Guo, J. Ordieres-Meré, Discovering the patterns of energy consumption, GDP, and CO2 emissions in China using the cluster method, Energy 166 (2019) 1149–1167.
[30] J. Wang, M. Hu, A. Tukker, J.F. Rodrigues, The impact of regional convergence in energy-intensive industries on China's CO2 emissions and emission goals, Energy Econ. 80 (2019) 512–523.
[31] V. Andreoni, S. Galmarini, Decoupling economic growth from carbon dioxide emissions: a decomposition analysis of Italian energy consumption, Energy 44 (1) (2012) 682–691.
[32] B.W. Ang, B. Su, Carbon emission intensity in electricity production: a global analysis, Energy Pol. 94 (2016) 56–63.
[33] S. Kim, S.K. Kim, Decomposition analysis of the greenhouse gas emissions in Korea's electricity generation sector, Carbon Manag. 7 (5–6) (2016) 249–260.
[34] J.F. Rodrigues, J. Wang, P. Behrens, P. de Boer, Drivers of CO2 emissions from electricity generation in the European Union 2000–2015, Renew. Sustain. Energy Rev. 133 (2020) 110104.
[35] J.M. Cansino, A. Sánchez-Braza, M.L. Rodríguez-Arévalo, Driving forces of Spain′ s CO2 emissions: a LMDI decomposition approach, Renew. Sustain. Energy Rev. 48 (2015) 749–759.
[36] K. Mohlin, J.R. Camuzeaux, A. Muller, M. Schneider, G. Wagner, Factoring in the forgotten role of renewables in CO2 emission trends using decomposition analysis, Energy Pol. 116 (2018) 290–296.
[37] M.Y. Raza, L.I. Dongsheng, Analysis of energy-related CO2 emissions in Pakistan: carbon source and carbon damage decomposition analysis, Environ. Sci. Pollut. Control Ser. (2023) 1–13.
[38] Q. Wang, R. Jiang, Is carbon emission growth decoupled from economic growth in emerging countries? New insights from labor and investment effects, J. Clean. Prod. 248 (2020) 119188.
[39] M.A. Russo, D. Carvalho, N. Martins, A. Monteiro, Future perspectives for wind and solar electricity production under high-resolution climate change scenarios, J. Clean. Prod. 404 (2023) 136997.
[40] J. Wang, C. Song, R. Yuan, CO2 emissions from electricity generation in China during 1997–2040: the roles of energy transition and thermal power generation efficiency, Sci. Total Environ. 773 (2021) 145026.
[41] H. Wang, P. Zhou, B.C. Xie, N. Zhang, Assessing drivers of CO2 emissions in China's electricity sector: a metafrontier production-theoretical decomposition analysis, Eur. J. Oper. Res. 275 (3) (2019) 1096–1107.
[42] Q. Yan, Q. Zhang, X. Zou, Decomposition analysis of carbon dioxide emissions in China's regional thermal electricity generation, 2000–2020, Energy 112 (2016) 788–794.
[43] N. Liu, Z. Ma, J. Kang, A regional analysis of carbon intensities of electricity generation in China, Energy Econ. 67 (2017) 268–277.
[44] B. Chen, J.S. Li, S.L. Zhou, Q. Yang, G.Q. Chen, GHG emissions embodied in Macao's internal energy consumption and external trade: driving forces via decomposition analysis, Renew. Sustain. Energy Rev. 82 (2018) 4100–4106.
[45] B. Lin, X. Lei, Carbon emissions reduction in China's food industry, Energy Pol. 86 (2015) 483–492.
[46] C. Zhang, Y. Zhao, C. Shi, Y.H. Chiu, Can China achieve its water use peaking in 2030? A scenario analysis based on LMDI and Monte Carlo method, J. Clean. Prod. 278 (2021) 123214.
[47] C. Duan, B. Chen, Driving factors of water-energy nexus in China, Appl. Energy 257 (2020) 113984.
[48] Q. Wang, S. Wang, Carbon emission and economic output of China's marine fishery–a decoupling efforts analysis, Mar. Pol. 135 (2022) 104831.
[49] X. Zhao, M. Jiang, W. Zhang, Decoupling between economic development and carbon emissions and its driving factors: evidence from China, Int. J. Environ. Res. Publ. Health 19 (5) (2022) 2893.
[50] J.F. Dong, C. Deng, X.M. Wang, X.L. Zhang, Multilevel index decomposition of energy-related carbon emissions and their decoupling from economic growth in Northwest China, Energies 9 (9) (2016) 680.
[51] B. Lin, X. Ouyang, Analysis of energy-related CO2 (carbon dioxide) emissions and reduction potential in the Chinese non-metallic mineral products industry, Energy 68 (2014) 688–697.
[52] J. Wang, Z. Li, T. Wu, S. Wu, T. Yin, The decoupling analysis of CO2 emissions from power generation in Chinese provincial power sector, Energy 255 (2022) 124488.
[53] M. Zhang, X. Liu, W. Wang, M. Zhou, Decomposition analysis of CO2 emissions from electricity generation in China, Energy Pol. 52 (2013) 159–165.
[54] M.Y. Raza, S. Tang, Inter-fuel substitution, technical change, and carbon mitigation potential in Pakistan: perspectives of environmental analysis, Energies 15 (22) (2022) 8758.
[55] X. Peng, X. Tao, K. Feng, K. Hubacek, Drivers toward a low-carbon electricity system in China's provinces, Environ. Sci. Technol. 54 (9) (2020) 5774–5782.
[56] M. Ma, X. Ma, W. Cai, W. Cai, Carbon-dioxide mitigation in the residential building sector: a household scale-based assessment, Energy Convers. Manag. 198 (2019) 111915.
[57] J.H. Xu, T. Fleiter, W. Eichhammer, Y. Fan, Energy consumption and CO2 emissions in China's cement industry: a perspective from LMDI decomposition analysis, Energy Pol. 50 (2012) 821–832.
[58] S.W. Tseng, Analysis of energy-related carbon emissions in Inner Mongolia, China, Sustainability 11 (24) (2019) 7008.
[59] P. Zhou, B.W. Ang, Decomposition of aggregate CO2 emissions: a production-theoretical approach, Energy Econ. 30 (3) (2008) 1054–1067.
[60] N. Abhyankar, J. Lin, F. Kahrl, S. Yin, U. Paliwal, X. Liu, A. Phadke, Achieving an 80% carbon-free electricity system in China by 2035, iScience 25 (10) (2022).
[61] P. Tapio, Towards a theory of decoupling: degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001, Transport Pol. 12 (2) (2005) 137–151.
[62] J.B. Ang, CO2 emissions, energy consumption, and output in France, Energy Pol. 35 (10) (2007) 4772–4778.
[63] H. Wang, B.W. Ang, B. Su, Assessing drivers of economy-wide energy use and emissions: IDA versus SDA, Energy Pol. 107 (2017) 585–599.
[64] B.W. Ang, T. Goh, Index decomposition analysis for comparing emission scenarios: applications and challenges, Energy Econ. 83 (2019) 74–87.
[65] P. Yu, H. Ma, Y. Yang, X. Li, D. Mba, A novel grey incidence decision-making method based on close degree and its application in manufacturing industry upgrading, J. Grey Syst. 32 (2) (2020).
[66] M.H. Pesaran, Y. Shin, R.J. Smith, Bounds testing approaches to the analysis of level relationships, J. Appl. Econom. 16 (3) (2001) 289–326. https://www.jstor.org/stable/2678547.
[67] Wendong Wei, et al., Decoupling relationship between energy consumption and economic growth in China's provinces from the perspective of resource security, Resour. Pol. 68 (2020) 101693.
[68] D. Fang, B. Yu, Driving mechanism and decoupling effect of PM2. 5 emissions: empirical evidence from China's industrial sector, Energy Pol. 149 (2021) 112017.
[69] J. Engo, Decoupling analysis of CO2 emissions from transport sector in Cameroon, Sustain. Cities Soc. 51 (2019) 101732.
[70] B. Lin, M.Y. Raza, Analysis of electricity consumption in Pakistan using index decomposition and decoupling approach, Energy 214 (2021) 118888.
[71] M. Karmellos, V. Kosmadakis, P. Dimas, A. Tsakanikas, N. Fylaktos, C. Taliotis, T. Zachariadis, A decomposition and decoupling analysis of carbon dioxide emissions from electricity generation: evidence from the EU-27 and the UK, Energy 231 (2021) 120861.
[72] Y. Song, M. Zhang, Using a new decoupling indicator (ZM decoupling indicator) to study the relationship between the economic growth and energy consumption in China, Nat. Hazards 88 (2017) 1013–1022.
[73] China Statistical Yearbook, 2021. www.stats.gov.cn/tjsj/ndsj/2021/indexeh.htm.
[74] B. Gu, X. Tan, Y. Zeng, Z. Mu, CO2 emission reduction potential in China's electricity sector: scenario analysis based on LMDI decomposition, Energy Proc. 75 (2015) 2436–2447.
[75] M. Zhang, X. Liu, W. Wang, M. Zhou, Decomposition analysis of CO2 emissions from electricity generation in China, Energy Pol. 52 (2013) 159–165.
[76] H. Song, G. Hou, S. Xu, CO2 emissions in China under electricity substitution: influencing factors and decoupling effects, Urban Clim. 47 (2023) 101365.
[77] T. Huo, Y. Ma, T. Yu, W. Cai, B. Liu, H. Ren, Decoupling and decomposition analysis of residential building carbon emissions from residential income: evidence from the provincial level in China, Environ. Impact Assess. Rev. 86 (2021) 106487.
[78] A. Chapman, S. Okushima, Engendering an inclusive low-carbon energy transition in Japan: considering the perspectives and awareness of the energy poor, Energy Pol. 135 (2019) 111017.
[79] M.Y. Raza, B. Lin, Renewable energy substitution and energy technology impact in a transitional economy: a perspective from Pakistan, J. Clean. Prod. (2022) 132163.
[80] B. Loewen, Coal, green growth and crises: exploring three European Union policy responses to regional energy transitions, Energy Res. Social Sci. 93 (2022) 102849.
[81] H. Jiemin, W. Chen, The impact of private sector energy investment, innovation and energy consumption on China's carbon emissions, Renew. Energy 195 (C) (2022) 1291–1299.
[82] M.Y. Raza, B. Lin, Future outlook and influencing factors analysis of natural gas consumption in Bangladesh: an economic and policy perspectives, Energy Pol. 173 (2023) 113379.