Received: 3 April 2021 | Revised: 24 September 2022 | Accepted: 17 December 2022

DOI: 10.1002/ijfe.2765

RESEARCH ARTICLE

WILEY

Demographic efficiency drivers in the Chinese energy production chain: A hybrid neural multi-activity network data envelopment analysis

Yue Zhao[1] | Jorge Antunes[1] | Yong Tan[2] | Peter Wanke[1]

[1]COPPEAD Graduate Business School, Federal University of Rio de Janeiro, Rio de Janeiro, Brazil

[2]School of Management, University of Bradford, Bradford, UK

Correspondence
Yong Tan, School of Management, University of Bradford, Bradford, West Yorkshire BD7 1DP, UK.
Email: y.tan9@bradford.ac.uk

Abstract

For meeting the external requirements of the Paris Agreement and reducing energy consumption per gross domestic product, China needs to improve its energy efficiency. Although the existing studies have attempted to investigate energy efficiency from different perspectives, little effort has yet been made to consider the collaboration among different stages in the production chain to produce energy outputs. In addition, various studies have also examined the determinants of energy efficiency, however, they mainly focused on technology and economic factors, no study has yet proposed and considered the influence of geographical factors on energy efficiency. In this article, we fill in the gap and make theoretical and empirical contributions to the literature. In this study, a two-stage analysis method is used to analyse energy efficiency and the influencing factors in China between 2009 and 2021. More specifically, from the theoretical/methodological perspective, a multi-activity network data envelopment analysis model is used to measure energy efficiency of different processes in the energy production chain. From the empirical perspective, we attempt to investigate the influence of geographical factors on energy efficiency through a neural network analysis. Meanwhile, the comparisons among different provinces are made. The result shows that the overall energy efficiency is low in China, and China relies more on the traditional energy industry than the clean energy industry. The efficiency level experiences a level of volatility over the examined period. Finally, we find that raw fuel pre-process and industry have a significant and positive impact on energy efficiency in China.

KEYWORDS

artificial neural networks, China, data envelopment analysis, demographic efficiency drivers, energy efficiency

1 | INTRODUCTION

China is the second largest economy in the world. Meanwhile, China is the largest country of energy consumption and the largest country in terms of carbon emissions worldwide (Cheng et al., 2020). China has established a series of policies to develop a sustainable green energy economy (Yan & Su, 2020) while setting its goal for fighting climate change by 2050 to be consistent with the Paris Agreement (Burandt et al., 2019). Similarly, the national and local governments, which are the key stakeholders of the energy industry, need to increase the sustainability of energy consumption (Burandt et al., 2019). From the international perspective, energy efficiency connects with economic competitiveness and sustainability in the world, which makes the study of energy production chains very relevant and necessary (Wang et al., 2019).

The previous studies show that China has a lower level of energy efficiency than the one of the European countries (Wang et al., 2019). Using a sample of 71 countries over the period 1990–2014, Sun et al. (2019) find that governmental institutional backing and green innovation have a strong and positive influence on energy efficiency. Bai et al. (2019) also show that there is a positive influence of government research and development (R&D) funding on green innovation efficiency of the energy-intensive industries. In this scenario, eco-efficiency is the key concept to assess the trade-offs between maximized energy productions and minimized environmental influence (Chen et al., 2020).

In China, different provinces and cities have unbalanced development on the economy and environment (Cheng et al., 2020; Li & Hu, 2012). It is found that the regional energy efficiency is related to the level of per capita gross domestic product (GDP) of that region. Research shows that the eastern area is ranked higher in ecological total-factor energy efficiency, while the central area is in the middle, and the western area has the lowest efficiency (Cheng et al., 2020; Li & Hu, 2012). The inequality of energy efficiency still exists in different cities, and the influencing factors include geography, city features, and strategic development (Zhang & Zhou, 2020). When energy efficiency is analysed, both production and distribution of economic outputs need to be considered. China uses excessive energy because of the economic inefficiency in different areas (Iftikhar et al., 2018).

To achieve sustainable development from the energy perspective, technology efficiency and innovation efficiency are usually used to design a path to low-pollutant processes in the energy-productive chains (Yan & Su, 2020). The current article uses a multi-activity network data envelopment analysis (MNDEA) model to analyse the energy efficiency of different processes in the energy production chain, taking into consideration a comprehensive view on several drivers, such as fixed/variable production cost ratios, raw fuel pre-processes, alternative uses for industry and heating, and its overall impact in terms of pollutant emissions. The country and different provinces' situations are also analysed using a set of socio-demographic variables.

Compared with the previous research, this article makes contributions to the multiple activities in series that occur in an energy production chain, rather than focusing on the traditional single-stage or black-box DEA analysis. In order words, we make significant contributions to the literature from the methodological/theoretical perspective by proposing a MNDEA, which benefits from the advantages of being able to consider the collaboration among different stages in the production chain. Besides, other energy efficiency papers focus more on the influence of institutional policies and investment of R&D, this article considers different socio-demographic variables that are pertinent to each province, including GDP, consumer pricing index (CPI), birth rate, and students' number in different educational institutions. In addition to the previous methodological/theoretical contributions, we fill in the gap in the literature from the empirical perspective by investigating the influence of demographical characteristics of different provinces in China on energy efficiency through a neural network analysis. The conclusion shows that raw fuel pre-processes and industry have a positive relationship with energy efficiency in China.

In summary, the objectives of the current study that we aim to achieve are: (1) investigate energy efficiency of the production chain using a sample of provincial data over the period 2009–2021 under an innovative MNDEA. Comparing to the previous studies, not only we would be able to obtain the overall efficiency level, but also, we would be able to obtain the efficiency levels of different processes in the production chain; (2) we investigate the impact of geographical characteristics on energy efficiency under a neural network analysis. This is supposed to provide more practical implications for the policy-making purposes.

2 | LITERATURE REVIEW

2.1 | Contextual setting

China needs to make its energy consumption more efficient for fulfilling its commitment to reduce carbon emissions. According to the Paris Agreement, China predicts that the emissions of CO_2 will be in the peak around 2030, and China will target its renewable energy share to 20%. Zhou et al. (2019) claim that if China insists its pathway on moving from fossil fuel energy consumption to renewable energy consumption and applying technology to make energy consumption more efficient, it will not only reduce the emission of CO_2, but also meet the requirement of the Paris Agreement. According to the National Energy Administration (2016), China's 13th Renewable Energy Development Five-Year Plan (FYP) (2016–2020) aims to increase its non-fossil energy consumption to 20% on its overall share. On the 13th FYP for Energy Development, China has emphasized its aim for building a decarbonized and more efficient energy system. The 13th FYP for Energy Development clearly states that energy consumption increases by more than 2.5% per year, but the energy consumption per GDP decreases by 15%. The plan also aims to limit coal consumption to under 58%. Among the plan's seven tasks, it uses four times 'revolution', including consumption revolution, supplier revolution, technology revolution, and energy system revolution. In addition to the 13th Energy Development Plan, China also has a significant improvement in funding for supporting the developments in the energy management field. Liu and Wang (2020) compare the size of funding for supporting energy improvement programs between the 12th FYP and the 13th FYP. In the energy management field, the funding increases from 21% to 24% from the 12th FYP to the 13th FYP. The development of green decarbonization in China is one of the prioritized areas that the strategic funding will focus on in the 13th FYP. Under the external and internal requirements, energy productive efficiency is important for China to achieve its sustainability goals.

2.2 | Previous related studies

Environmental and economic factors inspire countries worldwide to take more actions on energy efficiency. Mardani et al. (2017) categorize different DEA methods on energy efficiency estimation among 144 published scholarly papers in high-ranking journals and claim that DEA is a good tool for evaluating energy efficiency. DEA is a model for performance evaluation, and it is a non-parametric method that does not need to set prior assumptions (Jia & Liu, 2012). However, the traditional black box DEA model does not consider the inner structure (Liu & Wang, 2015). In the previous literature, scholars have taken different methods, including traditional DEA, Grey method and Slack-based DEA, two-stage double bootstrap DEA, and multiplicative network DEA to measure energy efficiency for different countries/regions (Jebali et al., 2017; Moon & Min, 2017; Ouyang & Yang, 2020; Wang et al., 2019).

In China, Li and Hu (2012), Jia and Liu (2012), Zhou et al. (2019), Zhao et al. (2019), Shang et al. (2020) use DEA or its related model to evaluate energy efficiency. Li and Hu (2012) adopt a SBM (Slack-based measure) model to evaluate eco total factor energy efficiency (ETFEE). Comparing to the traditional measurement that only considers GDP, Li and Hu (2012) also consider the undesirable output of CO_2 and SO_2 emissions. They find that the overall ETFEE was low in China between 2005 and 2009. Yu et al. (2019) use the meta-slack-based model analysis to evaluate energy efficiency. The findings show that government intervention and market openness have negative relationships with energy efficiency. Yu et al. (2019) address the issue of discriminatory power on the frontier when applying a slack-based model. Zhao et al. (2019) adopt a three-stage analysis to evaluate the level of energy efficiency at a province level. According to the features of different provinces, specific strategies are needed to enhance energy efficiency, which reflects the unbalanced development of different provinces. Different from the previous studies, Wanke et al. (2020) investigate energy efficiency in China through a robust Bayesian stochastic frontier analysis. In addition to the proposal of the innovative method, the study further examines the influence of business environment on energy efficiency. The findings suggest that financial sector development and competition have a significant and positive impact on energy efficiency. Rather than using the non-parametric or parametric method, Hou et al. (2020) proxy energy efficiency using energy intensity. The study further examines the impact of energy price, industrial structure, environmental regulation, R&D investment and foreign direct investment through both linear and nonlinear analyses. The findings suggest that the impact of energy price on energy efficiency depends on the level of environmental regulation and economic growth.

Li and Hu (2012) claim that the eastern area in China has higher ETFEE scores than ones of the central and western areas. They further reveal that there is a positive relationship between ETFEE and R&D investment. For the latest research, Zhang and Zhou (2020) use the Shephard energy distance function and the 'double' stochastic meta-frontier to analyse energy efficiency. They find that there is a gap in the efficiency levels among different groups of cities, and regional heterogeneity is one of the influencing factors of efficiency. Using a panel data of 30 provinces in China over the period 2008–2018, Wang et al. (2022) investigate energy efficiency under a Super-SBM model with undesirable outputs. The findings show that there is a level of difference in energy efficiency among the provinces. The study further finds that energy endowment has a significant and negative impact on energy efficiency, and environmental regulation plays a positive mediating role in the relationship. Using the super-efficiency DEA, Wang et al. (2021) investigate energy efficiency in China at the province level. The results suggest that the eastern area has the highest level of energy efficiency, followed by the central and western areas, the efficiencies of which are 0.812, 0.534, and 0.349, respectively. The study further adopts the Theil index to analyse the difference and change of regional energy efficiency. The study suffers from the limitation that there is no second-stage analysis to investigate the determinants of energy efficiency. Table 1 provides a summary of the previous research on energy efficiency. We can see that the previous studies mainly focus on

TABLE 1 Synthesized table of previous research

No.	Authors	Study location	Sample size	Time period	Methodology	Major conclusions
1	Li and Hu (2012)	China	30 regions	2005–2009	SBM-DEA	China's regional ETFEE was low, and extreme unbalances in regional energy efficiency exist. R&D investment and the level of dependence on foreign investment have positive relationships with regional energy efficiency.
2	Jia and Liu (2012)	China	30 provinces	2004–2010	DEA model + Tobit model	Beijing and the coastal southern cities have higher energy efficiency than the central and western areas; per capita GDP, the proportion of tertiary industry, and the urbanization rate affect energy/environment efficiency.
3	Goto et al. (2014)	International	47 prefectures in Japan	2002–2008	DEA model	Environmental regulation benefits the performance of the Japanese industries; the emission of greenhouse gases is a main source of inefficiency.
4	Huang et al. (2014)	China	30 regions	2000–2010	GB-US-SBM	The average eco-efficiency displays a normally distributed V-shape and there is a large gap in the efficiency level among different areas.
5	Li and Lin (2015)	China	29 provinces	1996–2012	Combination of super-efficiency and sequential DEA models	China's improvement in energy intensity differs significantly among different areas and the eastern area has the highest level of energy technology.
6	Liu and Wang (2015)	China	30 provinces	2008–2014	Network DEA model + Adjusted efficiency decomposition approach	The inner structure and the associated energy utilization properties can be characterized by the model.
7	Jebali et al. (2017)	International	24 countries	2009–2012	Two-stage double bootstrap DEA	The energy efficiency levels in the Mediterranean countries are high but decline over time. Gross national income per capita, population density, and renewable energy use impact energy efficiency.
8	Iftikhar et al. (2018)	International	19 major economies	2015	Network DEA	More than 80% of energy consumption and CO_2 emissions are derived from economic and distributive inefficiencies. China skews on economic inefficiency, and the US skews on distributive inefficiency.
9	Zhou et al. (2019)	China	38 industries	2010–2014	New DEA model (using an exponential transformation)	Most sectors do not perform well, especially the sectors related to energy extraction.
10	Yu et al. (2019)	China	30 regions	2006–2016	Meta-Frontier Method + SBM	Decoupling relationships between energy consumption and economic growth are displayed in provinces; The eastern areas have a higher level of energy efficiency. State intervention and market openness have negative impacts on energy efficiency.

TABLE 1 (Continued)

No.	Authors	Study location	Sample size	Time period	Methodology	Major conclusions
11	Wang et al. (2019)	International	25 countries	2008–2017	GM (the grey method) and SBM-DEA	Although European countries are found to be energy efficient, the inefficiency is explained by excessive energy consumption.
12	Zhao et al. (2019)	China	30 provinces	2008–2016	Three-stage DEA	The provincial energy efficiencies are significantly affected by the economic and energy consumption structure, the urbanization process, and the technical innovation level.
13	Du et al. (2019)	China	30 provinces	2009–2016	Two-stage network DEA	Green innovation efficiency of the Chinese industrial enterprises shows significant regional imbalances and differences. Green innovation efficiency has a positive relationship with energy efficiency.
14	Sun et al. (2019)	International	71 developed and developing countries	1990–2014	Parametric stochastic frontier approach based on the shepherd distance function	There is a positive influence of both green innovation and institutional quality on energy efficiency.
15	Chen et al. (2020)	China	30 regions	2000–2012	Multiplicative relational network DEA model + window analysis	There is a significant level of heterogeneity among the provinces for environmental sustainability and eco-efficiency indices, unbalanced production efficiency is found.
16	Zhang and Zhou (2020)	China	284 cities	2003–2013	The Shephard energy distance function + the 'double' stochastic meta-frontier	The regional heterogeneity has a significant impact on energy efficiency; the levels of energy efficiency vary under different group criteria, which highlights the importance of the specified criterion and technology heterogeneity.
17	Cheng et al. (2020)	China	30 provinces	1997–2016	DEA + Meta-frontier method	The eastern region is the most energy-efficient area, followed by the central and western areas, the inefficiency is attributed to poor management.
18	Qi et al. (2020)	China	14 major Chinese coal-intensive industries	2006–2015	Super-efficiency model of DEA	Total-factor energy efficiency shows a trend of growth from 2006 to 2015 and technology innovation has an important impact on energy efficiency.
19	Ouyang and Yang (2020)	International	27 OECD countries	2014	Multiplicative network DEA model	The multiplicative model is more reasonable in calculating regional energy and environmental efficiency than the traditional DEA model. The networked analytical structure can give policymakers more detailed analysis than the single process method.
20	Shang et al. (2020)	China	Thirty provinces and municipalities	2005–2016	SBM-DEA	There is a spillover effect of TFEE across different provinces in the region.
21	Wanke et al. (2020)	China	128 energy companies	2012–2015	Robust Bayesian stochastic Frontier analysis	There is a large dispersion in the efficiency level, while financial sector development and competition improve energy efficiency.

(Continues)

TABLE 1 (Continued)

No.	Authors	Study location	Sample size	Time period	Methodology	Major conclusions
22	Hou et al. (2020)	China	30 provinces	2003–2017	Energy intensity	The impact of energy price on energy efficiency is positive and the influence is affected by the level of environmental regulation and economic growth.
23	Wang et al. (2021)	China	30 provinces	2007–2019	Super-efficiency DEA	The eastern area has the highest energy efficiency, followed by the central area and the western area.
24	Wang et al. (2022)	China	30 provinces	2008–2018	Super-SBM model with undesirable outputs	There is a level of difference in energy efficiency among the provinces and energy endowment has a negative impact on energy efficiency, while this relationship is moderated by environmental regulation.

measuring regional energy efficiencies in China or the comparisons between different countries on energy efficiency. Meanwhile, the influencing factors, such as governmental policies and technological innovation, are also discussed (Du et al., 2019; Li & Lin, 2015; Zhang & Zhou, 2020). In terms of the methods adopted by the previous studies, more scholars realize that the traditional DEA model has limitations on considering undesirable outputs and relevant advancements based on the traditional DEA model have been made.

Concerning the DEA models from the literature, very limited efforts have been made to apply the DEA model to address the issue of multiplicate activities in the efficiency analysis. A MNDEA model is used by Yu and Lin (2008) to analyse the efficiency level of the railway industry. Wanke et al. (2018) use a super-efficiency MNDEA model with undesirable outputs to investigate the drivers of railway performance. Ouyang and Yang (2020) point out that the traditional DEA model assumes that variables are independent, but variables in the energy productions chain need to collaborate to produce the outputs, and the MNDEA model would be able to find out which activity is the main source of (in)efficiency in the production process.

Through reviewing the literature, we can see that the previous studies have adopted various methods in measuring energy efficiency. However, one area that has not yet been concerned by the previous studies is the consideration of collaboration among different stages in the production chain in the modelling framework. We can observe that different studies have also used various methods in the second stage to analyse the determinants of energy efficiency. We can see that the existing studies mainly focus on the environmental, business, and technological factors. However, little attempt has yet been made to consider the impact of geographical characteristics on energy efficiency. We fill in the gap in the literature by making methodological and empirical contributions. More specifically, we are the pioneer to analyse energy efficiency considering the production chain by proposing a MNDEA. From the empirical perspective, we attempt to investigate the influence of geographical characteristics on energy efficiency, which is supposed to provide more practical implications for the policy making purposes.

3 | METHODOLOGY

Very often, productive structures may not only be characterized by a set of individual processes in displayed in series, but also each one of these processes may be composed of individual stages or activities that share common productive resources. While the computation of technical efficiency in such circumstances may impose additional modelling complexity, the derivation of the improvement paths for each sub-structure may require a better understanding on how contextual variables may specifically affect them. In fact, the energy production and consumption structure, relying on different energetic sources, such as coal, oil, water and being generated and distributed to diverse uses, such as industrial or residential, constitute an idiosyncratic case where these shared sources and uses present different demographic dynamics while generating negative impacts on the environment in terms of harmful gas emissions. This particular structure requires a specific non-parametric efficiency model capable of handling productive networks structured in series and in parallel for capturing how such inputs and outputs are collectively used and generated.

Another distinctive feature of this article is the use of neural network regression models to unveil the impact of demographic variables on the efficiency scores of each productive energy substructure at the province level in China. Neural networks were introduced as way to resolve the limitations of the traditional econometric approaches, being able to handle numerous predictors while unveil the non-linear interactions that may exist among them and the variable to be predicted. Besides, the existence of shared inputs and outputs in the energy productive chain yields the efficiency estimates for each substructure of the energy network that are definitely correlating to one another, deeming for other approaches than the classic econometric ones.

Hence, the next subsections present and discuss the methodological choices adopted in this research to tackle the problem of measuring the demographic impacts on the energy chain efficiency at the province level in China, given its different sources and uses. Subsection 3.1 revisits one of the most used MNDEA models in productive networks, with previous applications in infrastructure and other economic sectors (Chen, 2017; Yu et al., 2016; Yu & Lin, 2008). Subsection 3.2 depicts the data sources and presents their major descriptive statistics, not only for the major inputs and outputs constituents of the energy productive network in China, but also for related demographic variables. Subsection 3.3 presents the developed MNDEA model for the Chinese energy sector based on the variables previously described. At last, Subsection 3.4 provides further details on the neural network modelling approach adopted in this research.

3.1 | The MNDEA model

The advantage of the MNDEA model is that it does not need any functional assumptions before modelling (Jia & Liu, 2012). DMUs (decisions-making units) can function well to transform inputs into outputs. However, the traditional DEA model is a single stage or black-box process. For analysing the sustainability of the energy production chain, a multi-activity 'M' (different activities in parallel) and/or network 'N' (different activities in series) DEA model allows the identification of specific weaknesses and strengths of the energy production chain to make it function in its most efficient way. We can also compute how much the shared inputs are split up among different operations.

The MDEA model was discussed in Beasley (1995) and subsequently extended in Molinero (1996). Specifically, this research departs from Tsai and Molinero (2002), where a classic DEA model is enhanced to accommodate a multi-activity network productive structure formed by a number of processes organized in series (cf. Figure 1). The overall efficiency score is computed by multiplying the individual efficiencies for each process in series, which, in turn, can be composed of distinct stages (activities) organized in parallel. The activities within each process can present their own technology frontier, while sharing common inputs in different proportions. In addition, their outputs may be jointly used in the subsequent process. At each process, the efficiencies are computed by means of additive weighted averages of the efficiencies obtained at each stage.

Let us suppose that there are $k\,(k=1, \ldots, K)$ DMUs that performs I activities or stages. Let $X_k^1, X_k^2, \ldots, X_k^I$ and $X_k^s = \left(x_{k,1}^s, x_{k,2}^s, \ldots, x_{k,L}^s\right)$ denote, respectively, the input set and their consumption shares for DMU k. X_k^i represents the input vector of the ith activity, while $x_{k,l}^s$ is the share of the lth input that is consumed by the I activities. Each $x_{k,l}^s$ can be turned into the ratio form, $\mu_{k,l}^i$, so that $\left(0<\mu_{k,l}^i<1, \sum_{i=1}^{I}\mu_{k,l}^i=1\right)$. In fact, each $\mu_{k,l}^i$ corresponds to a decision-variable for each DMU. Hence, the ith activity uses X_k^i and $\mu_k^i X_k^s$ to jointly produce desirable output Y_k^i and undesirable output B_k^i, in which $\mu_k^i X_k^s = \left(\mu_{k,1}^i x_{k,1}^s, \mu_{k,2}^i x_{k,2}^s, \ldots, \mu_{k,L}^i x_{k,L}^s\right)$, $Y_k^i = \left(y_{k,1}^i, y_{k,2}^i, \ldots, y_{k,M_i}^i\right)$, and $B_k^i = \left(b_{k,1}^i, b_{k,2}^i, \ldots, b_{k,R_i}^i\right)$. This notation can be expanded to represent a network structure composed of K processes. Therefore, the optimal MNDEA scores are the solution to the non-linear problem presented next:

$$
\begin{gathered}
\operatorname{Max}\rho^{j'} = \prod_{k=1}^{K}\sum_{i=1}^{I} w^{k,i}\rho_{j'}^{k,i} \\
s.t. \\
\sum_{j=1}^{J}\lambda_j^{k,i} Y_{j,m_i}^{k,i} \geq \left(1+\rho_{j'}^{k,i}\right) Y_{j',m_i}^{k,i}\ \forall k, \forall i, \forall m_i \\
\sum_{j=1}^{J}\lambda_j^{k,i} B_{j,r_i}^{k,i} = \left(1-\rho_{j'}^{k,i}\right) B_{j',r_i}^{k,i}\ \forall k, \forall i, \forall r_i \\
\sum_{j=1}^{J}\lambda_j^{k,i} x_{j,l_i}^{k,i} \leq \left(1-\rho_{j'}^{k,i}\right) x_{j',l_i}^{k,i}\ \forall k, \forall i, \forall l_i \\
\sum_{i=1}^{I}\sum_{j=1}^{J}\lambda_j^{k,i}\mu_{j',s}^{k,i} x_{j,s}^{k,s} \leq \sum_{i=1}^{I}\left(1-\rho_{j'}^{k,i}\right)\mu_{j',s}^{k,i} x_{j',s}^{k,s}\ \forall k, \forall s \\
\sum_{i=1}^{I}\mu_{j',s}^{k,i} = 1\ \forall k, \forall s \\
\sum_{j=1}^{J}\lambda_j^{k,i} = 1\ \forall k, \forall i \\
\lambda_j^{k,i} \geq \varepsilon \forall k,\ \forall i, \forall j \\
0.3 \leq \mu_{j',s}^{k,i} \leq 0.7 \\
\rho_{j'}^{k,i} \geq 0
\end{gathered}
, \quad (1)
$$

where $\rho_{j'}^{k,i}$ is the efficiency for stage i in process k of DMU j'; $w^{k,i}$ is the stage i weight set in process k; $\mu_{j',l}^{k,i}$ is the share ratio of input l for stage i in process k for DMU j'; i is the stage numbers in process k; s is the shared input numbers in process k; l_i is the input number for stage i in process k; m_i is the desirable output number for stage i in process k; r_i is the undesirable output number for stage i in process k.

Readers should note that model (1) observes the variable returns to scale assumption. The constant returns to scale assumption is obtained by removing $\sum_{j=1}^{J} \lambda_j^{k,i} = 1, \forall k, \forall i$ from model (1). Following Yu and Lin (2008), the consumption trade-offs between distinct activities, which are represented by the values of $\mu_{j',l}^{k,i}$, are restricted within the range from 0.3 to 0.7. For each DMU, the efficiency of a given process is the weighted average of the efficiencies of their respective stages:

$$\mathrm{TIE}_{j'}^{k} = \rho^{k,j'} = \sum_{i=1}^{I} w^{k,i} \rho_{j'}^{k,i}. \tag{2}$$

The weight $w^{k,i}$ represents the relative importance attributed to the activity (stage) i in process k. These weights have a sum value of 1 for each process k. The overall efficiency of DMU j' is the product of the efficiencies computed at each process:

$$\mathrm{TIE}_{j'} = \rho^{j'} = \prod_{k=1}^{K} \mathrm{TIE}_{j'}^{k}. \tag{3}$$

The technical efficiency of stage i in process k can be calculated as:

$$\mathrm{TE}_{j'}^{k} = 1 - \rho^{k,j'}. \tag{4}$$

We can extend to the overall technical efficiency as:

$$\mathrm{TE}_{j'} = 1 - \rho^{j'}. \tag{5}$$

3.2 | The data of the research

All direct and indirect data come from the National Bureau of Statistics of China. The period is used from 2009 to 2021. 16 variables including CAPEX (capital expenditure), OPEX (operating expenditure), and so on are used in the MNDEA model as Table 2 shows below. We evaluate all the variables through the R programming tools (R Core Team, 2020).

Table 2 lists all the variables in the energy production chain. In Figure 2, the energy production chain is described through four intermediate phases. Through different phases, we can compute and evaluate energy efficiency in the energy production chain. The period crosses four FYP in China. Therefore, the paper can evaluate the trend based on the country's energy management policies. The period from 2009 to 2010 is the last 2 years of the Eleventh FYP; The period during 2011–2015 is the whole process of the Twelfth FYP; The period during 2016–2020 is the whole process of the Thirteenth FYP, and 2021 is the first year of the fourteenth FYP.

In the second stage, through neural networks, contextual variables are considered to analyse the demographical factors' influence on the sustainability of the energy production chain. These factors, covering the areas of environment, population, education, economy, health, travel, are depicted in Table 3. After the evaluation of energy efficiency, the relationship between the following contextual variables and energy efficiency can be analysed.

3.3 | The model of research

Li and Hu (2012) point out that R&D investment and foreign investment have positive correlations with regional energy efficiency, and China has an unbalanced energy efficiency among different provinces. Therefore, in this research, we use contextual variables including education, industry and raw fuel pre-processes, since education

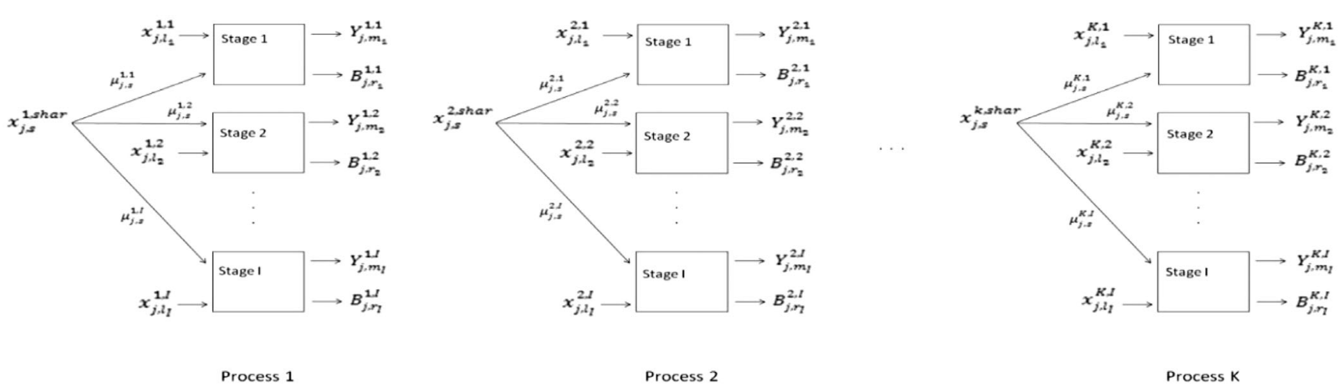

FIGURE 1 Generic representation of the efficiency MNDEA model for undesirable outputs with directional distance function.

TABLE 2 Descriptive statistics for MNDEA variables

Variable	Unit	Min	Max	Mean	SD	CV
CAPEX	100 million yuan	798.23	62,687.62	17,406.50	13,672.35	0.79
OPEX	100 million yuan	253.91	106,871.59	18,185.43	17,838.49	0.98
Coal	10,000 ton	0.00	64,073.74	14,422.59	11,241.10	0.78
Coke	10,000 ton	0.00	9904.22	1351.40	1642.17	1.22
Crude oil	10,000 ton	0.00	15,827.01	1810.87	2237.22	1.24
Diesel	10,000 ton	80.35	1814.34	589.80	349.97	0.59
Kerosene	10,000 ton	0.00	846.42	98.76	145.49	1.47
Fuel oil	10,000 ton	0.00	4686.43	183.83	528.61	2.88
Gasoline	10,000 ton	18.77	1756.15	438.58	314.07	0.72
Natural gas	10,000 ton	9.68	2727.15	546.19	469.02	0.86
LPG	10,000 ton	0.00	505.60	35.48	68.45	1.93
Hydro	100 million kWh	0.00	4087.19	348.71	633.31	1.82
Value added	100 million yuan	273.70	45,143.00	8498.19	8061.99	0.95
Hot water	MW	0.00	123,814.00	28,988.74	23,081.29	0.80
Steam	10,000 ton	22.78	27,231.34	4613.49	4711.35	1.02
CO_2	10,000 ton	1177.00	52,115.28	12,240.05	8607.01	0.70

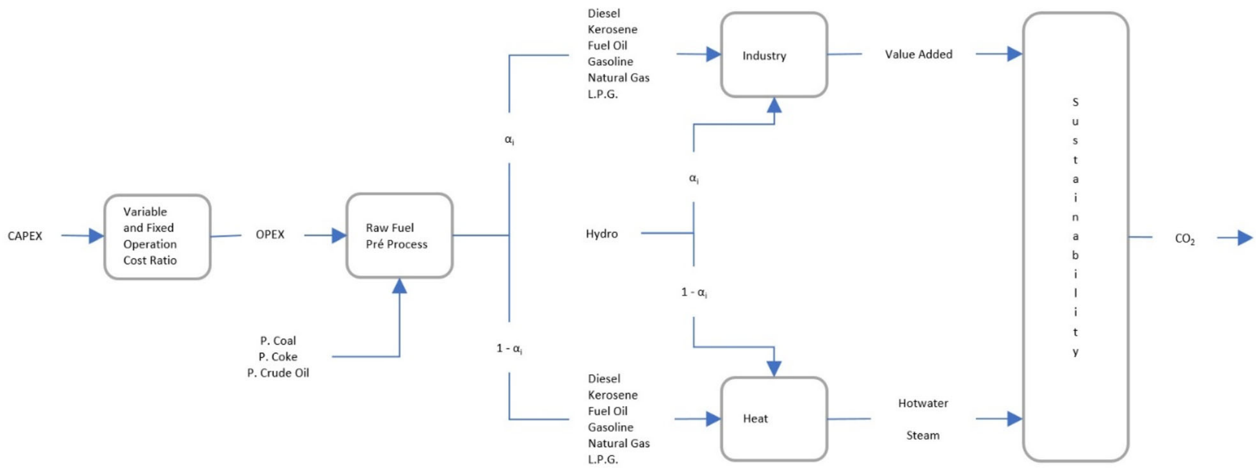

FIGURE 2 Chinese sustainability model [Colour figure can be viewed at wileyonlinelibrary.com]

would have an impact on technology and people's awareness about energy efficiency. For industry and raw fuel pre-processes, its development also depends on capital investment and technology development. Jia and Liu (2012) find that Beijing and the coastal southern provinces have higher levels of energy efficiencies, which are affected by their GDP and industrial levels. Zhao et al. (2019) also show that there is a significant imbalance among provinces in the level of energy efficiency, which is affected by technological innovation and the level of urbanization at the province level.

Therefore, in this research, GDP, CPI, and Gini index are also considered. Yu et al. (2019) discuss the impact of state intervention and market openness, which we do not consider since the overall evaluation would like to remind related parties, especially the country, to make better policies to improve energy efficiency in China. There are also contextual variables that have not been analysed yet, since the previous literature has not treated such variables thus far.

In the study, we use a hybrid neural-MNDEA model. First, we map the Chinese sustainability model, which is shown in Figure 2. In the first stage, through the MNDEA model, the energy production chain in China would be divided into four processes. In each part, the energy efficiency would be evaluated. From CAPEX to OPEX, energy efficiency in the variable and fixed production cost ratio is considered. Then, adding the coal, coke,

TABLE 3 Descriptive statistics for demographical variables

Descriptive stats	Unit	Min	Max	Mean	*SD*	CV
Cleaning area	10,000 m^2	1807.00	134,823.70	24,745.33	21,383.50	0.86
Birth rate	Births/1000 persons	5.36	17.89	11.19	2.65	0.24
City illiteracy	%	0.63	16.63	5.20	2.92	0.56
CPI	%	−2.30	6.30	2.23	1.43	0.64
Death rate	Deaths/1000 persons	4.09	7.99	6.09	0.79	0.13
City employed	%	12.52	42.92	21.17	5.15	0.24
Exchange in tourism	USD million	4.43	23,062.36	2355.51	3391.60	1.44
Garbage disposal	10,000 tons	66.25	3394.51	658.14	513.25	0.78
GDP PPP	yuan/Person	10,814.00	183,980.00	52,114.55	28,939.19	0.56
GDP	100 million yuan	939.70	124,369.70	23,977.71	21,007.87	0.88
GINI index	–	0.46	0.49	0.47	0.01	0.02
Health care institutions	Unit	4129.00	89,528.72	32,424.64	22,057.84	0.68
Students in higher education	Students/100,000 persons	1043.00	6410.00	2629.86	857.52	0.33
Students in Jr. secondary	Students/100,000 persons	1226.00	6146.00	3401.33	967.86	0.28
Students in primary education	Students/100,000 Persons	3045.18	12,046.00	7135.09	2030.72	0.28
Students in Sr. secondary	Students/100,000 persons	759.16	4931.00	3067.52	778.55	0.25
Students in kindergartens	Students/100,000 persons	1110.00	6983.09	2894.55	931.07	0.32
Passengers in highways	%	13.30	97.26	81.32	14.99	0.18
Passengers in railways	%	0.17	83.45	17.24	14.41	0.84
Passengers in waterways	%	0.00	14.78	1.44	2.19	1.52
Passengers total	10,000 persons	2474.00	574,266.00	72,746.93	70,582.02	0.97
Civil vehicles	10,000 vehicles	24.35	2981.30	574.10	514.09	0.90
Passenger vehicles	%	63.76	94.67	83.26	6.64	0.08
Resident population	10,000 persons	557.00	12,684.00	4579.13	2821.15	0.62
Urban population	%	29.88	89.58	58.27	12.79	0.22
City unemployed	%	0.39	2.57	1.11	0.40	0.36

and crude oil, energy efficiency in the raw fuel pre-processes is considered. After processing, all fuels are entered into the industry and heat sectors through the general energy we use in our production. Then, through added value and hot water steam, energy efficiency of the sustainability can be evaluated. The final input variable is CO_2. Besides the separate intermediate phases' energy efficiency, the overall energy efficiency would also be computed and evaluated through the country, different provinces, and the time trend. Then, through different energy consumption and energy efficiency, the optimal industry share in the country, different provinces, and the time trend are computed and evaluated. All the results are used to evaluate which phase needs to be improved more and it will also show the levels of efficiencies over the time trend.

Second, after the first-stage efficiency assessment of the Chinese energy production chain, the second stage focuses on the relationships between the contextual variables and the overall efficiency levels. These relationships are explored through artificial neural networks, where linear models are specified to assess the relative importance of each contextual variable so that policies and regulations could be designed. In this research, we particularly look at the MLP (multi-layer perceptron) network which stands among the most widely used methods in forecasting applications (Mubiru & Banda, 2008). A typical MLP is given in Figure 3.

Precisely, the connection weight approach described in Olden et al. (2004) and Olden and Jackson (2002) is used to assess the relative importance of each contextual variable on the overall efficiency level of the Chinese energy production chain. This approach accurately identifies the true importance of each contextual variable, altogether with the direction of its impact, whether positive or negative.

4 | RESULTS

According to the three-stage MNDEA model, based on the data from 2009 to 2021, three aspects have been analysed. First, through Figures 4–6, the overall energy efficiency in the energy production chain in China, efficiencies of each process by year and the situations in different provinces are analysed, respectively. Second, through Figures 7–9, the optimal industry share of energy sources by country, by the time trend and by provinces are analysed, respectively. Third, Figure 10 shows the result of the contextual variables which influence energy efficiency of the energy production chain.

4.1 | Energy efficiency in the energy production chain

4.1.1 | The overall energy efficiency in the energy production chain

In Figure 2, we calculate all transformation phases to evaluate the energy efficiency. From CAPEX to OPEX, the variable and fixed production cost ratios are calculated. Before all energy are applied to the industry and heat, the raw fuel pre-processes are evaluated. After its application, the sustainability is used to evaluate how much CO_2 is released. The country's energy efficiencies

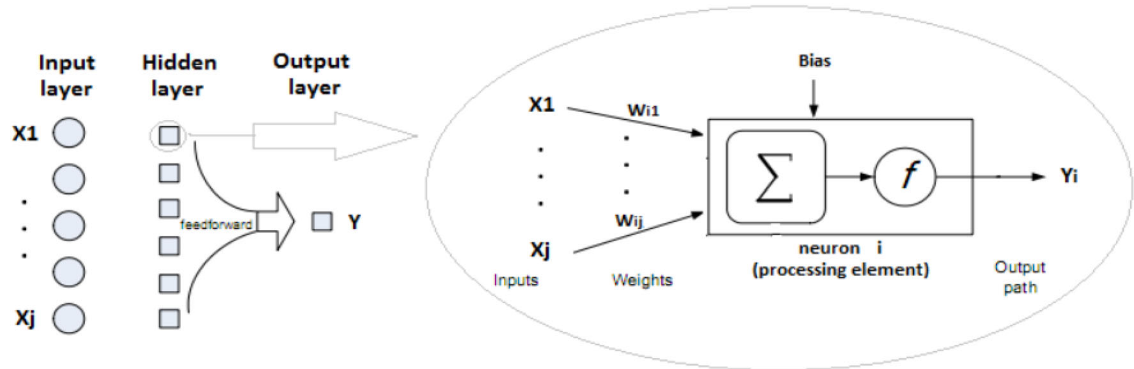

FIGURE 3 Example of an MLP (left) and details of a neuron from the hidden layer (right) [Colour figure can be viewed at wileyonlinelibrary.com]

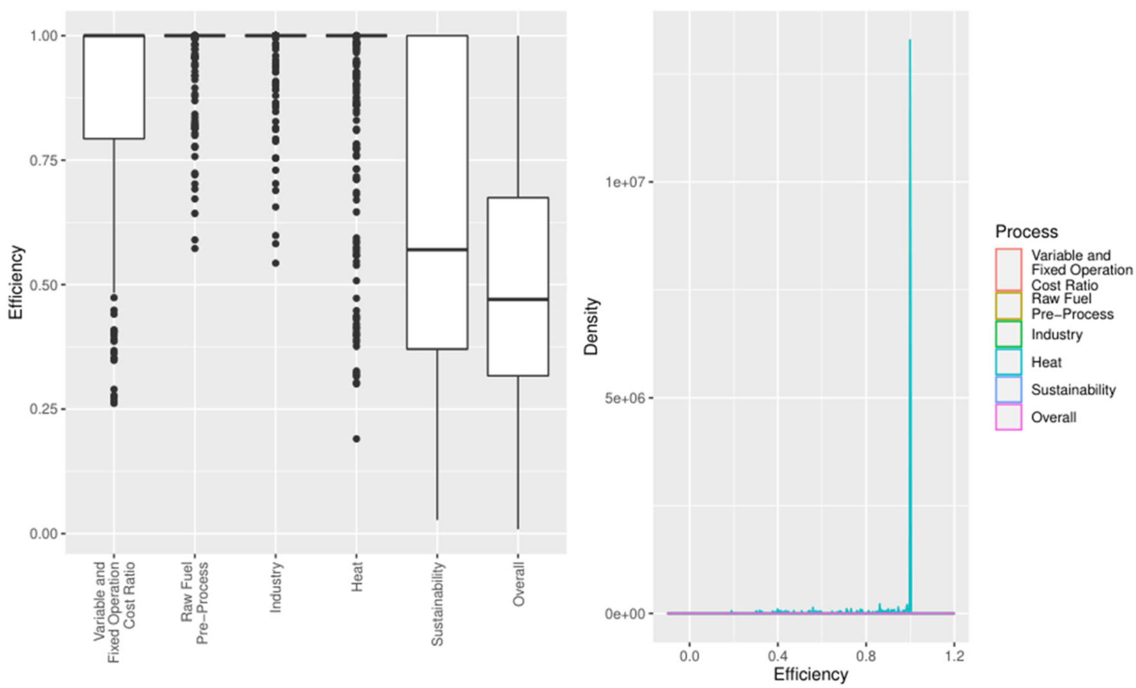

FIGURE 4 Energy efficiencies for each process (left: Boxplot; right: Density plot) [Colour figure can be viewed at wileyonlinelibrary.com]

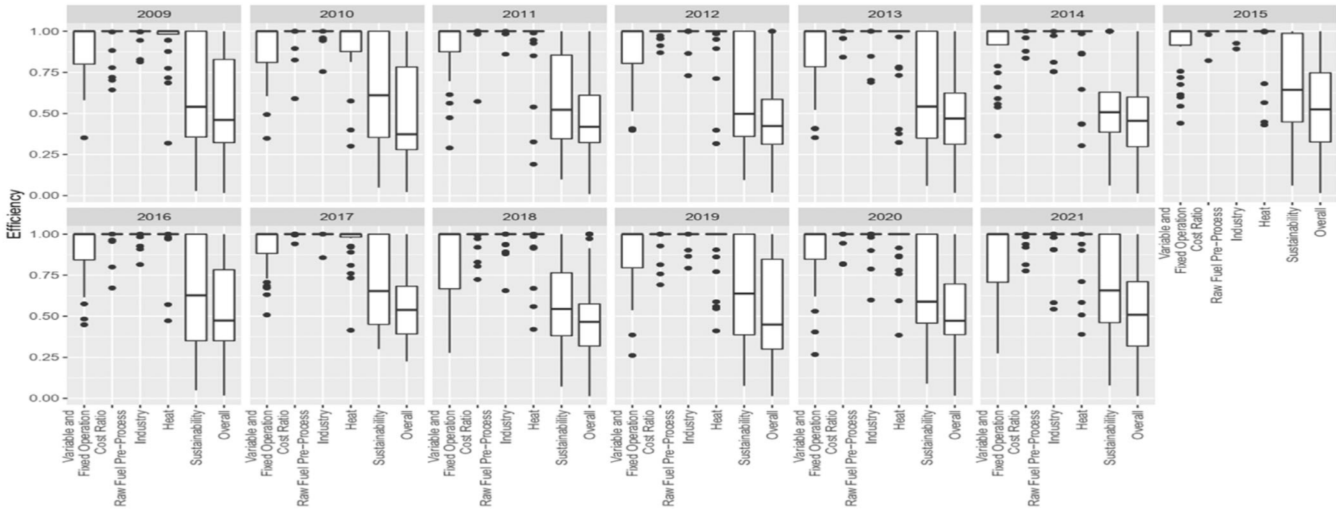

FIGURE 5 Boxplot of efficiencies for each process by year

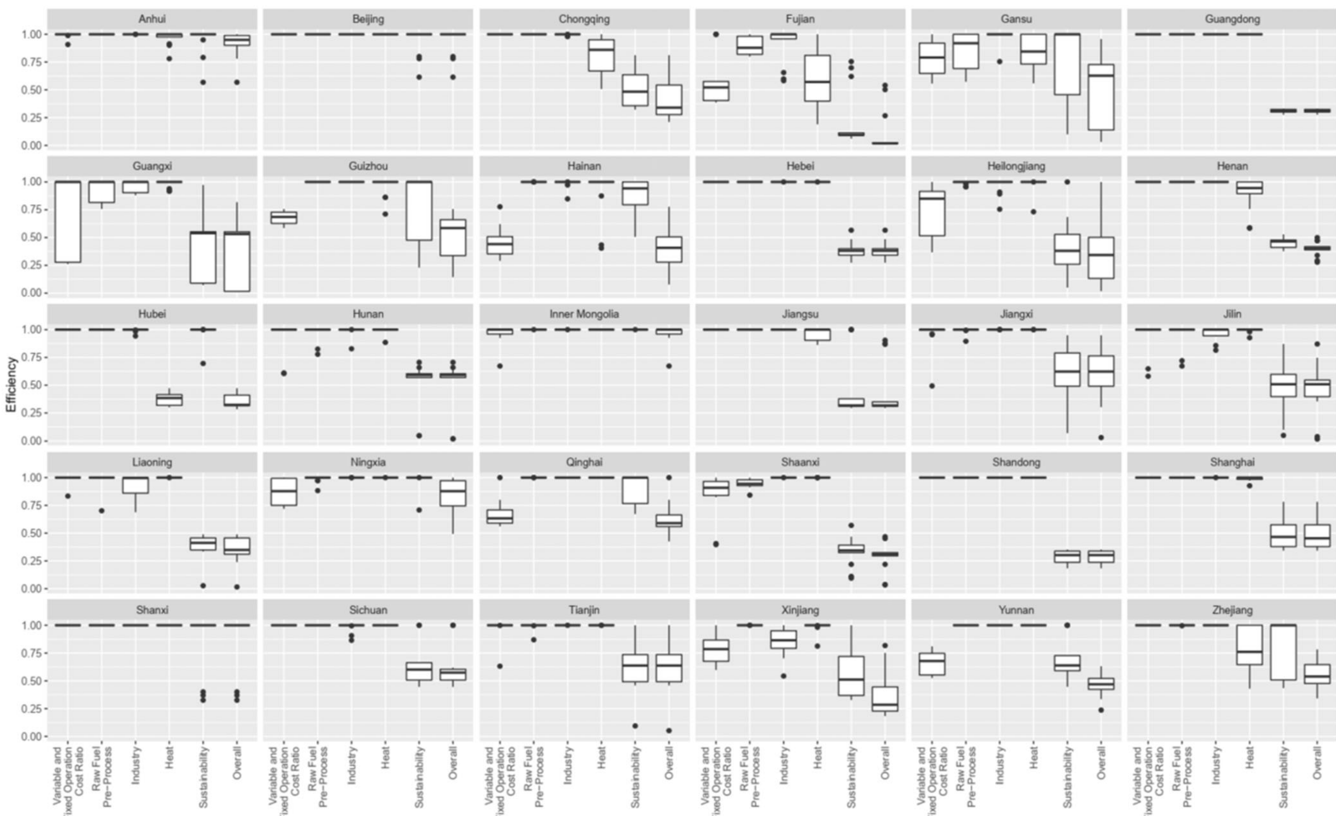

FIGURE 6 Boxplot of efficiencies for each process by provinces

of different processes are shown in Figure 4. It is shown that there is a level of heterogeneity in energy efficiency for different phases in the production chain and the overall energy efficiency is low. The median overall energy efficiency score in the boxplot is nearly 0.5, which is lower than all the other phases. Looking at the median values of different phases, the raw fuel pre-processes and the industry process are close to 1, displaying a relatively high level of energy efficiency. However, these two phases have numbers of outliers compared with other phases. The Heat shows the highest level of density in the density plot. Meanwhile, other phases' density is very small. The median value of the sustainability phase is around 0.6, which means that at the end of the energy production chain, it still displays the lower position of the overall energy efficiency. The Chinese overall energy efficiency and the level of sustainability are low. Our results are in contrast with Zhao and Hu (2020) who report a higher level of energy efficiency compared with us. The main difference is attributed to the fact that we use an advanced operational research method to derive the efficiency score, while Zhao and Hu (2020) retrieve the efficiency scores from the National Bureau of Statistics. This comparison also shed light that the statistics revealed by the Chinese authorities are lack of accuracy. The overall situation of energy efficiency is low in China, and it still has lots of space to improve, in particular, for the final phase. From the perspective of the energy production chain, the data depicts that from the value-add process in the industry and heat to the CO_2, the current working flow cannot work sustainably.

4.1.2 | The time trend of energy production chain

Figure 5 depicts the boxplot of energy efficiencies for each process on an annual basis. From 2009 to 2021, the energy consumption policies go from the last 2 years of the eleventh FYP to the whole thirteenth FYP, and then the year 2021 is the beginning year of the fourteenth FYP. From 2009 to 2021, China has progressed so much economically and increased its energy consumption. Based on the country's FYP, China has established different policies related to energy and the environment. From the eleventh FYP to the fourteenth FYP, it emphasizes more on clean energy and environmental protection, which would be better for the sustainability of energy consumption and improve the economic competitiveness. The inter-quartile range of the overall energy efficiency becomes narrower between 2011 and 2014. The minimum median of the boxplot is around 0.375 and the lower quartile experiences a slight volatility. In 2009, the lower quartile is slightly lower than 0.375, this is roughly the same case in 2021. Combining Figures 4 and 5, two figures depict that the overall energy efficiency in China is not high, and the efficiency experiences a level of volatility over the period. It means that the Chinese FYP related to energy development does not have a clear influence on the energy production chain and there is a room to improve. Our results are not in line with Zhu et al. (2020), who report that there is a positive influence of the FYPs on energy efficiency. This is mainly attributed to the different method we adopted in the current study. The sustainability phase keeps at a low level in energy efficiency, and the boxplot is taller than the other phases during 2009–2021, showing bigger differences among the provinces. The raw fuel pre-processes and the industry phase keep a high-level energy efficiency, closing to 1 in most of the years. For the beginning phase, which is the variable and fixed production cost ratio, the median efficiency level keeps at 1 over the examined period.

4.1.3 | Energy efficiencies by provinces

Figure 6 shows the boxplot of efficiencies for each process by provinces. 30 capital cities of the provinces show their interpreted results of energy efficiency in different phases in the energy production chains. Different provinces have different natural resources, industry features,

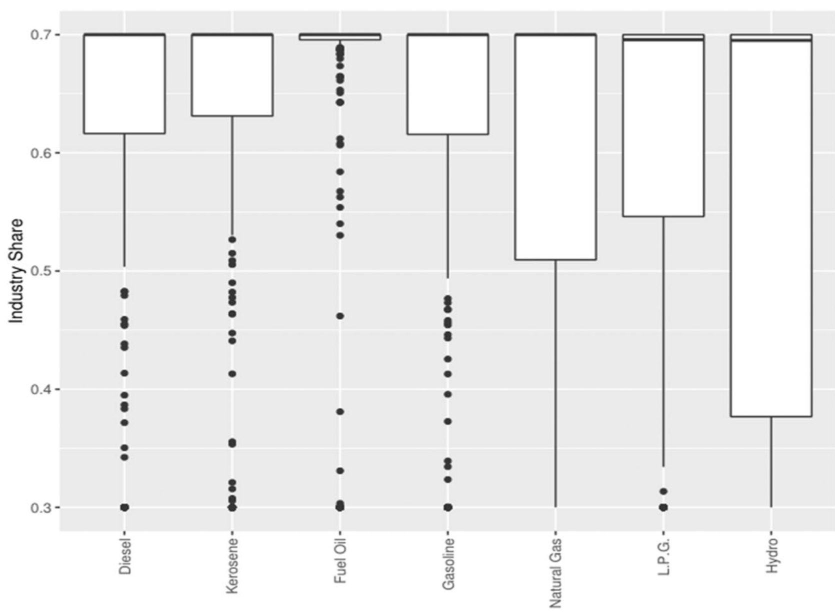

FIGURE 7 Boxplot of optimal industry share of energy sources

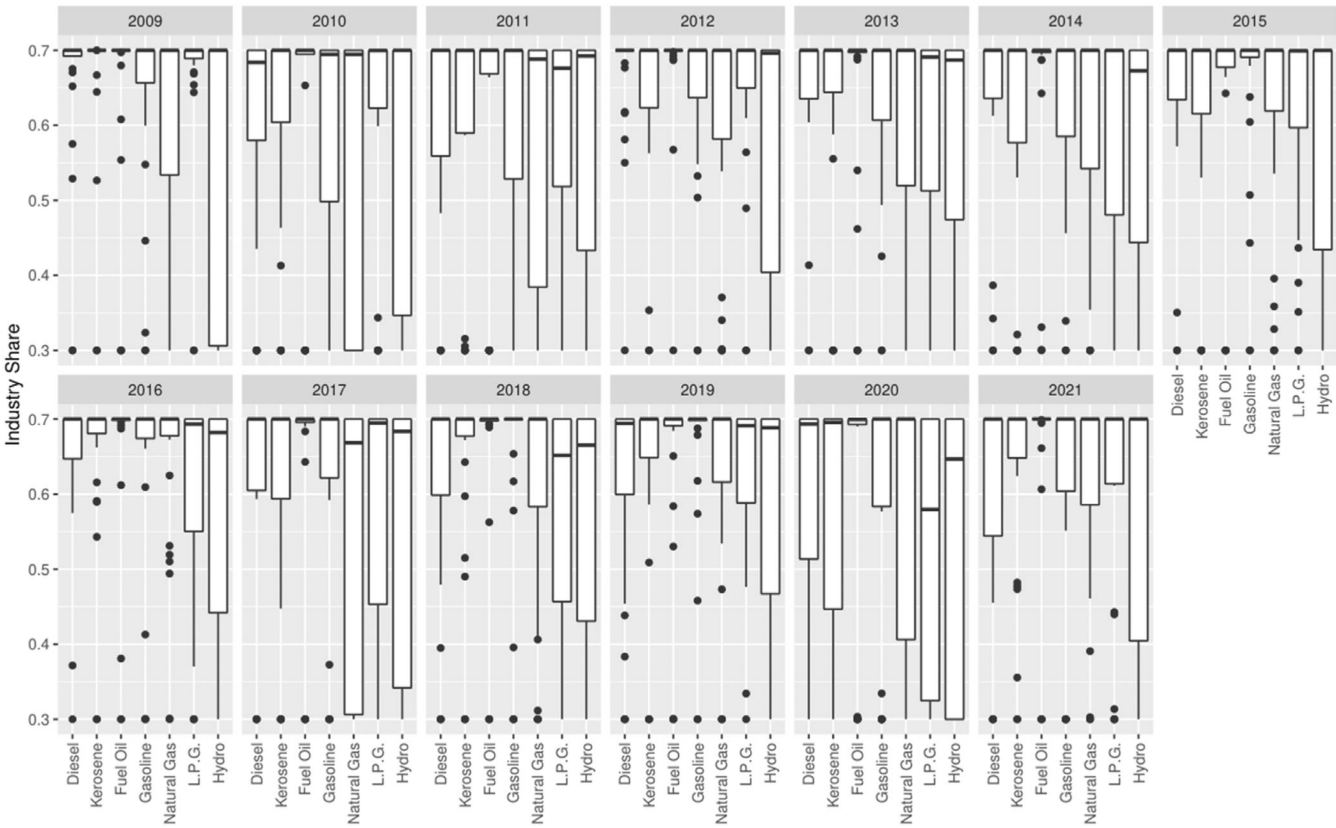

FIGURE 8 Boxplot of optimal industry share of energy source by year

and geographical features, so there are different characteristics in the phases of the energy production chain among them. For most cities, the sustainability score is consistent with the overall energy efficiency score. It means that if the provinces have higher levels of sustainability and fewer pollutant emissions, they have a higher overall energy efficiency score.

In terms of the results of all capital cities in different provinces, Beijing is the only city that has all phases with a high energy efficiency level. As the capital city in China, Beijing has more strict environmental regulations on industry and heat emissions, leading to fewer pollutants at the end of the energy production chain. Therefore, its sustainability and overall energy efficiency are better than other cities. Anhui, located in the central area of China, has all its phases' efficiency above 0.5 and has a short boxplot on sustainability and the overall efficiency, which is consistent with its development in the past years to attract lots of high technology industries. Our results show that the eastern area of China has higher ETFEE than the central and western areas. This finding is in line with Li and Hu (2012) as well as Cheng et al. (2020). The provinces in all three areas have good scores and bad scores. Most cities have low scores on sustainability and the overall energy efficiency scores. The cities in the eastern areas, including Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Shandong, and Guangdong, have higher energy efficiency than the ones in the central and western areas, such as Heilongjiang, Guizhou, Xinjiang, and Ningxia. Four out of 30 capital cities have tall boxplot (bigger than 0.25) on the variable and fixed production cost ratio, showing low energy production transformation, which would deteriorate energy efficiency.

4.2 | Optimal energy efficiency

4.2.1 | The overall optimal energy efficiency

Figure 7 depicts the boxplot of optimal industry share of energy sources using the data of various energy sources such as diesel, kerosene, fuel oil, gasoline, natural gas, L.P.G., and hydro. Fuel oil has the shortest interquartile, and hydro has the tallest interquartile. Except for natural gas and hydro, all the other sources have some outliers. Figure 4 indicates that the country relies heavily on fuel oil, and in terms of natural gas, which is clean energy, it has an unbalanced distribution in China. However, as clean energy, natural gas would be beneficial for the sustainability of the environment and the economy, so the distribution of industry share still has room for improvement.

4.2.2 | The time trend of optimal industry share of energy sources

The time trend of optimal industry share of energy sources is depicted in Figure 8. Over the examined period, we notice that the interquartile of fuel oil consistently keeps at a low level, which means that the country uses more fuel oil and develops its energy strategy towards a positive direction. The time trend of hydro displays good performance with most of its lower quartile more than 0.4. All the other energy sources experience a level of volatility in their interquartile over the examined period. For fuel oil, China relies on it the most among all the energy sources during the past years. It indicates that China does not develop their clean energy sufficiently.

4.2.3 | The optimal industry share of energy sources by provinces

Figure 9 depicts the boxplot of optimal industry share of energy sources by provinces. The distribution of optimal industry share shows a level of heterogeneity, which is different from the distribution of energy efficiency. Beijing shows the best performance in its distribution of energy sources and keeps a balance between traditional energy and clean energy. The result indicates that it has a strict policy to balance all the energy resources. The provinces such as Chongqing, Hainan, Qinghai, Xinjiang, and Yunnan have all their optimal industry shares, which are close to 0.7. These provinces cannot be divided by the level of economic development or based on the geographical factors. Chongqing has good economic performance compared with Hainan, Qinghai, and Xinjiang, which are separated as less developed cities, and may have a lower level of energy and environmental management. Different provinces have big differences in the optimal industry share compared with their energy efficiency. However, comparing between traditional energy and clean energy, almost all the provinces rely more on traditional energy and still have room to improve their optimal industry energy share. The whole distribution of optimal energy share is consistent with the trend of the overall sample.

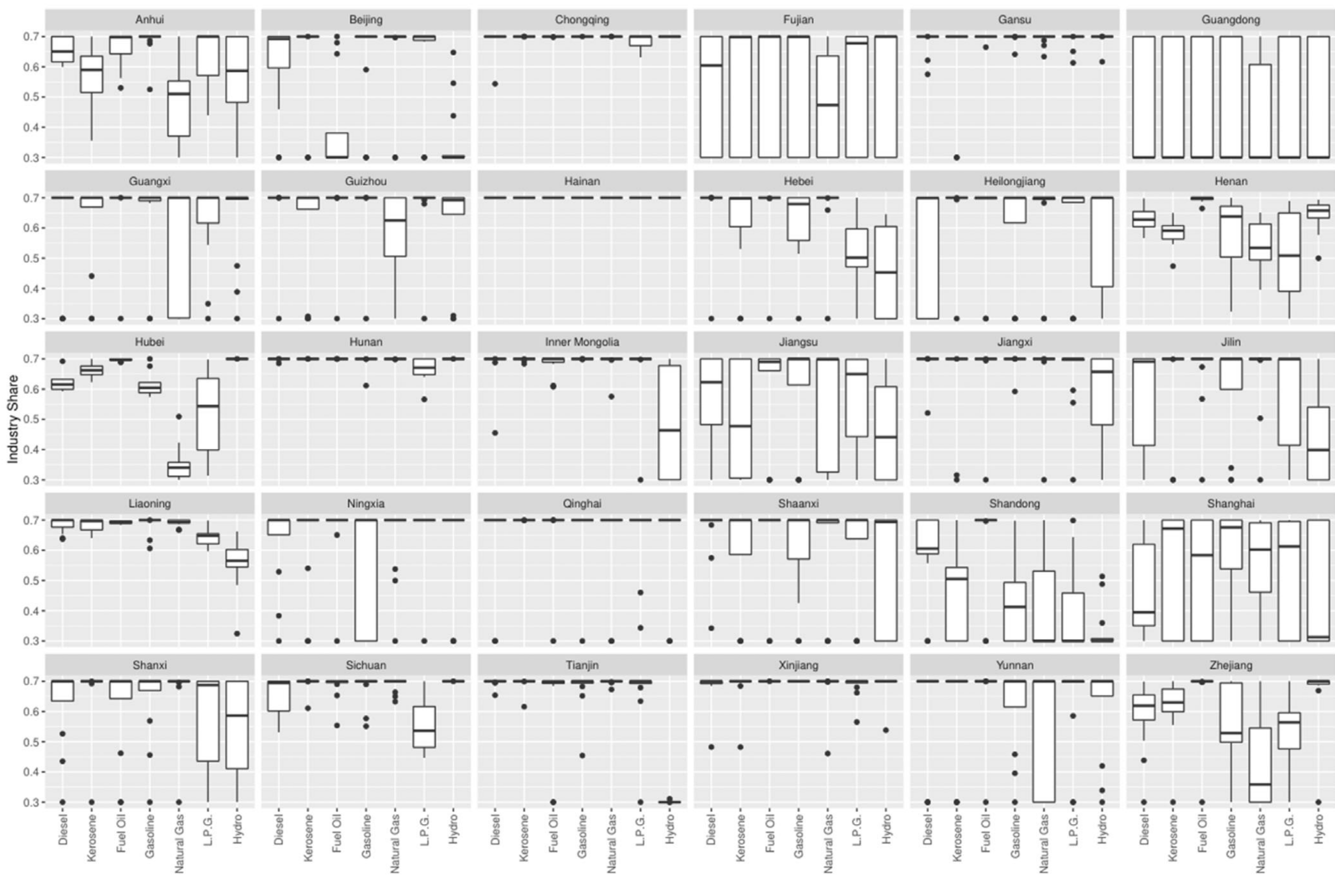

FIGURE 9 Boxplot of optimal industry share of energy sources by province

4.3 | Contextual variables importance related to energy efficiency

Figures 10 and 11 depict the contextual variables' importance for the energy production chain. We consider comprehensive contextual variables that are used by the previous studies, including GDP, birth rate, Gini Index, education-related index. Raw fuel pre-processes and Industry have a positive relationship with energy efficiency in the energy production chain. As shown previously, most of the provinces have a high score of energy efficiency on the phases of raw fuel pre-processes and

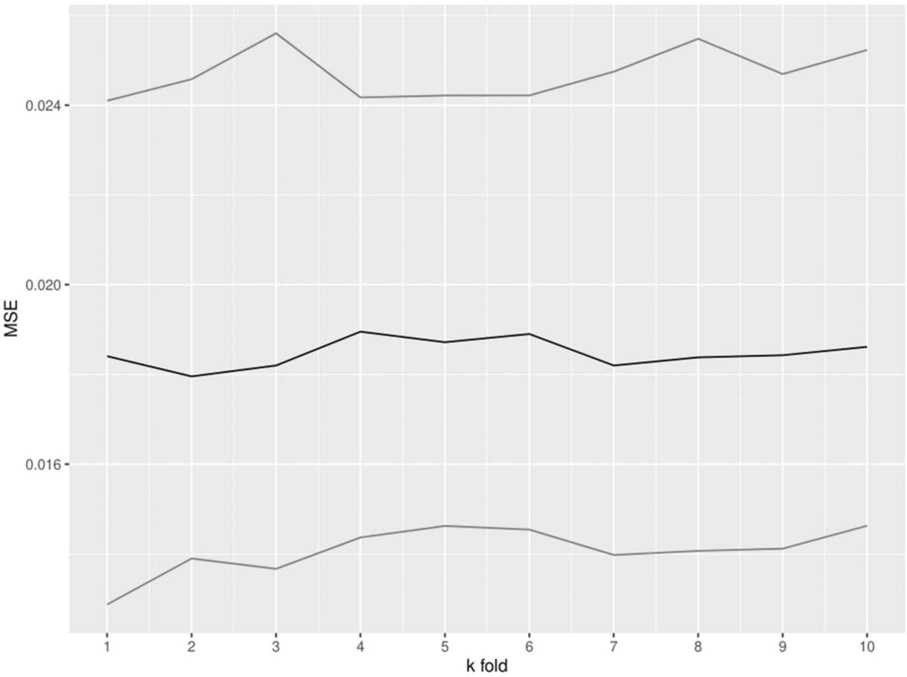

FIGURE 10 Mean squared error of 10-fold cross validation test in 100 training repetitions (95% of confidence interval).

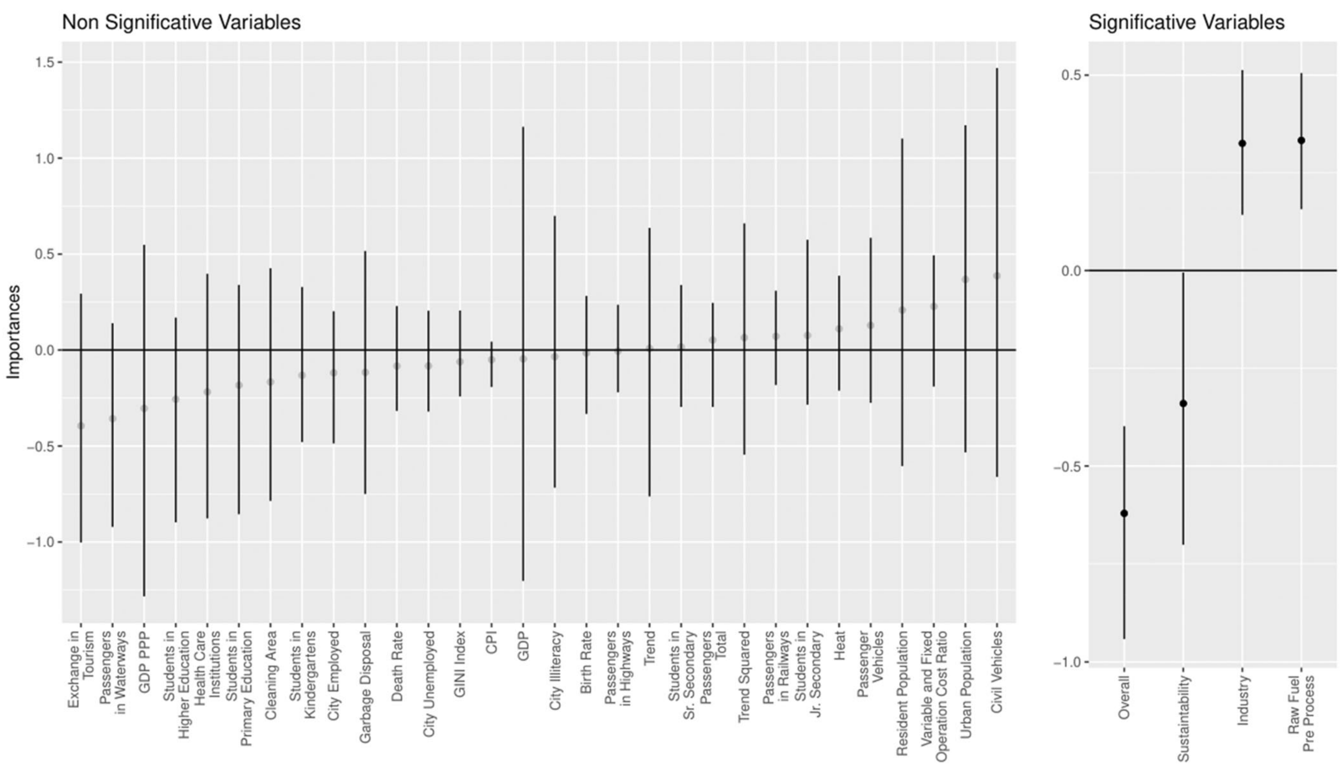

FIGURE 11 Contextual variables importance (95% confidence interval)

industry. The result indicates that more capital and technology are invested in developing the phases of raw fuel pre-processes and industry, which results in higher energy efficiency. The positive influence of investment on energy efficiency is in accordance with Haider and Mishra (2021).

5 | CONCLUSIONS

For evaluating the level of energy efficiency in China, we map the energy production chain and evaluate energy efficiency of the separate and overall phases through a MNDEA model. Using data from the National Bureau of Statistics in China, we compute and evaluate energy efficiency in China, in different provinces, and its time trend. And meanwhile, we also evaluate the optimal industry share of energy sources under the same approach.

From the perspective of energy efficiency, our research period covers the period between 2009 and 2021. It is shown that there is a level of heterogeneity in energy efficiency for different phases in the production chain, and the overall energy efficiency is low. The median overall energy efficiency score in the boxplot is nearly 0.5, which is lower than all the other phases. At the province level, almost all the provinces have different characteristics, especially the optimal industry share of energy sources. Much of the heterogeneity can be seen since they have different geographical factors. At the city level, our results show that Beijing, comparing to other provinces/cities in China, has better performance, this is in line with Wang et al. (2021). Our results further report that Anhui has an efficiency level of more than 0.8, which is in contrast with Wang et al. (2021), who report a slightly lower efficiency scores compared with ours. We attribute this difference to the fact that different methodologies to measure energy efficiency is adopted by the studies. From the perspective of geographical areas, our results show that the eastern area performs better than the central and western areas, this result is in accordance with Li and Hu (2012); Cheng et al. (2020). Finally, looking at the performance of the overall sample on an annual basis, our results show that the level of energy efficiency is not high during the examined period, and the efficiency experiences a level of volatility. This finding is different from Wang et al. (2022). Overall, over the examined period, the efficiency level achieved by the Chinese energy industry is slightly below 0.5, indicating that the efficiency level is low, and using the same amount of energy inputs, the generation of the outputs can be further expanded by at least 50%. With regard to different processes in the production chain, we can clearly observe that sustainability has relatively lower level of average efficiency, the score of which is about 0.6, indicating for this process specifically, the Chinese energy sector could further improve the performance by expanding the existing energy outputs by at least 40%.

Concerning energy efficiency, most of the provinces have better performance in the phases of raw fuel pre-processes and industry. Their sustainability and overall energy efficiency are consistent with the overall sample. In terms of the optimal industry share, we notice that there are bigger differences among the provinces in the sample. Overall, China lacks sustainability in the energy production chain and has an unbalance consumption of industry share on the energy sources. China also tries to transform its consumption from the traditional energy to the clean energy, although the process is slow during the past years.

The paper uses neural science to evaluate the importance of contextual variables for energy efficiency. Different from the previous research, we find that factors related to the economy have close relationships with energy efficiency. The result shows that raw fuel pre-processes and industry have positive relationships with energy efficiency. Raw fuel pre-processes and industry are important phases in the energy production chain.

In summary, we have the following policy implications: (1) in order to shorten the differences in the energy efficiency level among different provinces/cities in China, for the cities/areas with lower energy efficiency, it is recommended that the city or provincial government should further encourage the practice of research and innovation, in particular in the area of green innovation, this can be facilitated by allocating more funds to support these activities; (2) in order to shorten the differences in the energy efficiency among different geographical areas, government policy is recommended to made to provide favourable policies towards these areas in terms of providing more investment support to develop the energy industry in general and the renewable energy specifically; (3) Emphasis is recommended to be given to raw fuel pre-process and industry, the improvement in these two processes would positively contribute to the improvement in the overall energy efficiency in China.

The current study suffers from the following limitations: (1) although China is the biggest developing country in the world and investigating the energy efficiency is an important research topic, which has an impact on different level of the society, the current study to a certain extent is narrow because it did not consider other countries in the world, which may affect the accuracy and robustness of the results. (2) in the second-stage analysis investigating the impact of geographical characteristics on energy efficiency, a neural network analysis is proposed. However, the current study lacks a robustness check on this. Based on these limitations, in terms of the future studies, (1) efforts can be made to include more countries in the world in the sample to check the robustness of the results; (2) in terms of the second-stage analysis, alternative methods can be adopted to check the robustness of the results. There are alternative methods that can be alternatively used to double check the robustness of our results including the multi-layer perceptron–Hidden Markov Model approach (Tan et al., 2021) and the Robust endogenous neural network analysis (Antunes et al., 2021).

ACKNOWLEDGEMENT

The authors are very grateful to the anonymous reviewers for their and detailed and insightful suggestions.

CONFLICT OF INTEREST

The authors have declared no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Jorge Antunes https://orcid.org/0000-0003-3199-5912
Yong Tan https://orcid.org/0000-0002-3482-1574
Peter Wanke https://orcid.org/0000-0003-1395-8907

REFERENCES

Antunes, J., Had-Vencheh, A., Jamshidi, A., Tan, Y., & Wanke, P. (2021). Bank efficiency estimation in China: DEA-RENNA approach. *Annals of Operations Research*, *315*, 1373–1398. https://doi.org/10.1007/s10479-021-04111-2

Bai, Y., Song, S., Jiao, J., & Yang, R. (2019). The impacts of government R&D subsidies on green innovation: Evidence from Chinese energy-intensive firms. *Journal of Cleaner Production*, *233*, 819–829.

Beasley, J. E. (1995). Determining teaching and research efficiencies. *Journal of the Operational Research Society*, *46*, 441–452.

Burandt, T., Xiong, B., Löffler, K., & Oei, P. (2019). Decarbonizing China's energy system – Modeling the transformation of the electricity, transportation, heat, and industrial sectors. *Applied Energy*, *255*, 113820.

Chen, C. C. (2017). Measuring departmental and overall regional performance: Applying the multi-activity DEA model to Taiwan's cities/counties. *Omega*, *67*, 60–80.

Chen, Z., Kourtzidis, S., Tzeremes, P., & Tzeremes, N. (2020). A robust network DEA model for sustainability assessment: An application to Chinese provinces. *Operational Research*, *22*, 235–262. https://doi.org/10.1007/s12351-020-00553-x

Cheng, Z., Liu, J., Li, L., & Gu, X. (2020). Research on meta-frontier total-factor energy efficiency and its spatial convergence in Chinese provinces. *Energy Economics*, *86*, 104702.

Du, J.-L., Liu, Y., & Diao, W.-x. (2019). Assessing regional differences in green innovation efficiency of industrial enterprises in china. *International Journal of Environmental Research and Public Health*, *16*(6), 940.

Goto, M., Otsuka, A., & Sueyoshi, T. (2014). DEA (data envelopment analysis) assessment of operational and environmental efficiencies on Japanese regional industries. *Energy*, *66*, 535–549.

Haider, S., & Mishra, P. P. (2021). Does innovative capability enhance the energy efficiency of Indian iron and steel firms? A Bayesian stochastic frontier analysis. *Energy Economics*, *95*, 105128.

Hou, P., Li, Y., Tan, Y., & Hou, Y. (2020). Energy Price and energy efficiency in China: A linear and nonlinear empirical investigation. *Energies*, *13*, 4068.

Huang, J., Yang, X., Cheng, G., & Wang, S. (2014). A comprehensive eco-efficiency model and dynamics of regional eco-efficiency in China. *Journal of Cleaner Production*, *67*, 228–238.

Iftikhar, Y., Wang, Z., Zhang, B., & Wang, B. (2018). Energy and CO_2 emissions efficiency of major economies: A network DEA approach. *Energy*, *147*, 197–207.

Jebali, E., Essid, H., & Khraief, N. (2017). The analysis of energy efficiency of the Mediterranean countries: A two-stage double bootstrap DEA approach. *Energy*, *134*, 991–1000.

Jia, Y., & Liu, R. (2012). Study of the energy and environmental efficiency of the Chinese economy based on a DEA model. *Procedia Environmental Sciences*, *13*, 2256–2263.

Li, K., & Lin, B. (2015). The improvement gap in energy intensity: Analysis of China's thirty provincial regions using the improved DEA (data envelopment analysis) model. *Energy*, *84*, 589–599.

Li, L., & Hu, J. (2012). Ecological total-factor energy efficiency of regions in China. Retrieved July 17, 2020, from.

Liu, Y., & Wang, K. (2015). Energy efficiency of China's industry sector: An adjusted network DEA (data envelopment analysis)-based decomposition analysis. *Energy*, *93*, 1328–1337.

Liu, Z., & Wang, Q. (2020). Granted projects and Trend from National Natural Science Foundation of China in the field of energy and environmental management during the 13th five-year plan period. *Chinese Journal Of Environmental Management*, *12*, 20–27.

Mardani, A., Zavadskasb, E., Streimikienec, D., Jusoha, A., & Khoshnoudia, M. (2017). A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renewable and Sustainable Energy Reviews*, *70*, 1298–1322.

Molinero, C. M. (1996). On the joint determination of efficiencies in a data envelopment analysis context. *Journal of the Operational Research Society*, *47*, 1273–1279.

Moon, H., & Min, D. (2017). Assessing energy efficiency and the related policy implications for energy-intensive firms in Korea: DEA approach. *Energy*, *133*, 23–34.

Mubiru, J., & Banda, E. (2008). Estimation of monthly average daily global solar irradiation using artificial neural networks. *Solar Energy*, *82*, 181–187.

National Energy Administration. (2016). China 13th renewable energy development five year plan (2016–2020). Nea.gov.cn. Retrieved July 1, 2020, from http://www.nea.gov.cn/135916140_14821175123931n.pdf

Olden, J. D., & Jackson, D. A. (2002). Illuminating the black box: Understanding variable contributions in artificial neural networks. *Ecological Modelling*, *154*, 135–150.

Olden, J. D., Joy, M. K., & Death, R. G. (2004). An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecological Modelling*, *178*, 389–397.

Ouyang, W., & Yang, J. (2020). The network energy and environment efficiency analysis of 27 OECD countries: A multiplicative network DEA model. *Energy*, *197*, 117161.

Qi, X., Guo, P., Guo, Y., Liu, X., & Zhou, X. (2020). Understanding energy efficiency and its drivers: An empirical analysis of China's 14 coal intensive industries. *Energy*, *190*, 116354.

R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing https://www.R-project.org/

Shang, Y., Liu, H., & Lv, Y. (2020). Total factor energy efficiency in regions of China: An empirical analysis on SBM-DEA model with undesired generation. *Journal of King Saud University - Science*, *32*, 1925–1931.

Sun, H., Edziah, B., Sun, C., & Kporsu, A. (2019). Institutional quality, green innovation and energy efficiency. *Energy Policy*, *135*, 111002.

Tan, Y., Wanke, P., Antunes, J., & Emrouznejad, A. (2021). Unveiling endogeneity between competition and efficiency in Chinese banks: A two-stage network DEA and regression analysis. *Annals of Operations Research*, *306*, 131–171.

Tsai, P. F., & Molinero, C. M. (2002). A variable returns to scale data envelopment analysis model for the joint determination of efficiencies with an example of the UK health service. *European Journal of Operational Research*, *141*, 21–38.

Wang, C., Nguyen, T., & Yu, M. (2019). Energy use efficiency past-to-future evaluation: An international comparison. *Energies*, *12*, 3804.

Wang, R., Wang, Q., & Yao, S. (2021). Evaluation and difference analysis of regional energy efficiency in China under the carbon neutrality targets: Insights from DEA and Theil models. *Journal of Environmental Management*, *293*, 112958.

Wang, Y., Deng, X., Zhang, H., Liu, Y., Yue, T., & Liu, G. (2022). Energy endowment, environmental regulation, and energy efficiency: Evidence from China. *Technological Forecasting and Social Change*, *177*, 121528.

Wanke, P., Chen, Z., Liu, W., Antunes, J., & Azad, M. (2018). Investigating the drivers of railway performance: Evidence from selected Asian countries. *Habitat International*, *80*, 49–69.

Wanke, P., Tan, Y., Antunes, J., & Hadi-Vencheh, A. (2020). Business environment drivers and technical efficiency in the Chinese energy industry: A robust Bayesian stochastic frontier analysis. *Computers and Industrial Engineering*, *144*, 106587.

Yan, J., & Su, B. (2020). What drive the changes in China's energy consumption and intensity during 12th five-year plan period? *Energy Policy*, *140*, 111383.

Yu, J., Zhou, K., & Yang, S. (2019). Regional heterogeneity of China's energy efficiency in "new normal": A meta-frontier super-SBM analysis. *Energy Policy*, *134*, 110941.

Yu, M., Chen, L., & Hsiao, B. (2016). Dynamic performance assessment of bus transit with the multi-activity network structure. *Omega*, *60*, 15–25.

Yu, M., & Lin, E. (2008). Efficiency and effectiveness in railway performance using a multi-activity network DEA model. *Omega*, *36*, 1005–1017.

Zhang, N., & Zhou, M. (2020). The inequality of city-level energy efficiency for China. *Journal of Environmental Management*, *255*, 109843.

Zhao, H., Guo, S., & Zhao, H. (2019). Provincial energy efficiency of China quantified by three-stage data envelopment analysis. *Energy*, *166*, 96–107.

Zhao, X., & Hu, S. (2020). Does market-based electricity price affect China's energy efficiency? *Energy Economics*, *91*, 104909.

Zhou, Z., Xu, G., Wang, C., & Wu, J. (2019). Modeling undesirable output with a DEA approach based on an exponential transformation: An application to measure the energy efficiency of Chinese industry. *Journal of Cleaner Production*, *236*, 117717.

Zhu, B., Su, B., Li, Y., & Ng, T. S. (2020). Embodied energy and intensity in China's (normal and processing) exports and their driving forces, 2005-2015. *Energy Economics*, *91*, 104911.

How to cite this article: Zhao, Y., Antunes, J., Tan, Y., & Wanke, P. (2022). Demographic efficiency drivers in the Chinese energy production chain: A hybrid neural multi-activity network data envelopment analysis. *International Journal of Finance & Economics*, 1–19. https://doi.org/10.1002/ijfe.2765