UNIVERSIDADE FEDERAL DO RIO DE JANEIRO

INSTITUTO COPPEAD DE ADMINISTRAÇÃO

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Demographic Efficiency Drivers in the Chinese Energy Production Chain: A Hybrid Neural Multi-Activity Network Data Envelopment Analysis

Rio de Janeiro

2020

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TITLE: Demographic Efficiency Drivers in the Chinese Energy Production Chain: A Hybrid Neural Multi-Activity Network Data Envelopment Analysis

Master thesis presented to COPPEAD Graduante School of Business, Universidade Federal do Rio de Janeiro, as part of the mandatory requirements in order to obtain the degree of Masters in Business Administration (M. Sc.)

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CIP - Catalogação na Publicação

ZHAO, Yue
Zz63d Demographic Efficiency Drivers in the Chinese Energy Production Chain: A Hybrid Neural Multi Activity Network Data Envelopment Analysis / Yue ZHAO. -- Rio de Janeiro, 2021.
48 f.

Orientador: Peter Wanke.
Dissertação (mestrado) - Universidade Federal do Rio de Janeiro, Instituto COPPEAD de Administração, Programa de Pós-Graduação em Administração, 2021.

1. Energy Efficiency Analysis. 2. Energy Sustainability. I. Wanke, Peter, orient. II. Título.

Elaborado pelo Sistema de Geração Automática da UFRJ com os dados fornecidos pelo(a) autor(a), sob a responsabilidade de Miguel Romeu Amorim Neto - CRB-7/6283.

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Acknowledgement

It would not be possible to accomplish the present thesis without supports from many people. First, I would like to express my sincere gratitude to my supervisor, Prof. Peter Wanke, who leads me to the area of DEA analysis and guides me with the methodology for conducting research. Thanks for all his encouragement during the period to finish my thesis.

I would like to thank my colleague, Jorge Antunes , for his valuable suggestions and insightful comments, besides the knowledge related to my topic. I have learned a lot from the enthusiastic discussion with him. And his rigorous scientific attitude on research will have a profound influence on me.

Special thanks to Prof. Aaron Tan. Thank you for the sincere suggestions and help for my thesis and improve it better.

Many thanks also go to the staff of COPPEAD for all the help during my master's study.

Special thanks to all my friends. I feel very warm in such a foreign country because of their help. The talks on imagining the future, celebrations of various special days, and awesome traveling, made my life here much more colourful. The time living and studying together with them is my most precious memories in Rio de Janeiro.

Last, but certainly not least, to my family: my parents, thanks for their encouragement and support; my fiancé, Huarong Cheng, thanks for his warm companionship and

endless encouragement. I would not have reached this stage without their support.

Abstract

Energy efficiency has close connections with environmental and economic development in China. For meeting the external requirements of Paris Agreement and reducing energy consumption per GDP, China needs to improve its energy efficiency. In this paper, two-stage analysis method is used to analyse energy efficiency and influencing factors in China between 2009-2016. A Multi- Activity Network DEA (MNDEA) model is used to measure the energy efficiency of different processes in the energy production chain, and different demographic factors are considered through a neural network analysis. Meanwhile, the comparisons among different provinces are made. The research result shows that the overall energy efficiency is low in China, and relies more on traditional energy industry than clean energy industry. However, under the guidance of the Chinese government's five-year plan, the energy efficiency is improving, and the industry share of energy sources is transforming. Education related factors have importance on energy efficiency.

Keywords: Data Envelopment Analysis; Energy efficiency; China; Super-efficiency

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1.Introduction

China today is the second 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 with 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 economy competitiveness and sustainability in the world, which makes the study of energy production chains very relevant and necessary (Wang et al.,2019).

Previous studies show that China has a lower level of energy efficiency than the of ones of the European countries (Wang et al.,2019). Using a sample of 71 countries over the period 1990 to 2014, Sun et al. (2019) found 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 funding on the green innovation efficiency of energy-intensive industries. In this scenario, eco-efficiency is the key concept to assess the trade-offs between maximised energy productions and minimised environmental influence (Chen et al. 2020).

In China, different provinces and cities have unbalanced development on the economy and environment (Li and Hu. 2012; Cheng et al., 2020). it is found that the regional energy efficiency is related to the level of per capita GDP of that region. Research shows that the eastern area is ranked higher in ecological total-factor energy efficiency, and the northeast, central areas are in the middle, and the west area has the lowest efficiency (Li and Hu. 2012; Cheng et al., 2020).

Energy efficiency inequality today still exists in different cities, and the influencing factors include geography, city features, and strategic development.(Zhang & Zhou, 2020). When the energy efficiency is analysed, both production and distribution of economic outputs need to be considered. In fact, China uses excessive energy because of the economy inefficiency in different areas (Iftikhar et al., 2018).

To achieve a sustainable development in the energy area, technology efficiency and innovation efficiency are usually used to design a path to low-pollutant processes in energy productive chains (Yan & Su, 2020). The paper uses a Multi-activity Network Data Envelopment Analysis 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 productive cost ratios, raw fuel pre-processing, alternative uses for industry and heating, and its overall impact in terms of pollutant emissions. The country and different provinces' situations are also analysed in terms of a set of socio-demographic variables.

Compared to previous research, this paper 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. Besides, while other energy efficiency papers focus more on the influence of governmental institutional policies and investment of R&D, this paper considers different socio-demographic variables that are pertinent to each province, including GDP, CPI, birth rate, students' number in different educational institutions. The conclusion shows that raw fuel pre-process, industry, students' numbers in primary education and senior education have a positive relationship with Chinese energy efficiency.

2. Literature Review

2.1. Contextual Setting

China needs to make its energy consumption more efficient in its commitment to reduce carbon emissions. According to Paris Agreement, China predicts that 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 the energy consumption more efficiently and reduce emission of CO_2, China can meet its Paris Agreement's requirement. According to National Energy Administration (2016), China's 13^{th} Renewable Energy Development Five Year Plan (2016-2020) aims to increase its non-fossil energy consumption to 20% on its overall share. On the 13^{th} Five-Year Plan (FYP) for Energy Development, China has emphasized its aim for building a decarbonized, more energy efficient energy system. The 13th FYP Plan for Energy Development clearly states that the 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 the coal consumption under 58%. Among the plan's seven tasks, it uses four times "revolution", includes 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 & Wang (2020) compare the size of funding for supporting energy improvement programs between the 12th five-year plan and the 13th five-year plan period. In the energy management field, the funding increases from 21% to 24% from the 12th FYP to the 13th FYP. The development on 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) categorise different DEA methods about 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 which does not need to set priori assumptions (Jia & Liu, 2012). However, traditional black box DEA model does take inner structure into consideration. (Liu & Wang, 2015). In previous literature, scholars have taken different methods including traditional DEA, Grey method and Slack-based DEA, two-stage double bootstrap DEA, multiplicative network DEA to measure energy efficiency for different countries/regions (Moon and Min, 2017; Jebali et al., 2017; Wang et al., 2019; Ouyang and Yang, 2020).

In China, Li and Hu (2012), Jia & Liu (2012), Zhou et al., (2019), Zhao et al., (2019), Shang et al., (2020) use DEA model or its related model like SBM-DEA model to evaluate energy efficiency. Li and Hu (2012) adopted 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 considers undesirable output of CO_2 and SO_2 emissions and find that the overall ETFEE was low in China between 2005 and 2009. Yu et al., (2019) use a meta-slack-based model analysis to evaluate the energy efficiency and find that the government intervention and market openness have negative relationships with energy efficiency. Yu et al. (2019) addresses 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.

Li and Hu (2012) claim that the eastern areas in China have higher ETFEE scores than the one of the middle and western areas and reveal that there is a positive relationship between ETFEE and R&D investment as well as foreign investment. For the latest research, Zhang & Zhou (2020) use the Shephard energy distance function and the “double” stochastic meta-frontier to analyse energy efficiency and find that there is a gap in efficiency levels among different groups of cities and regional heterogeneity is one of the influencing factors of efficiency. Table 1 provides a summary of previous research about energy efficiency. We can see that the previous studies mainly focus on measuring regional energy efficiencies in China or comparisons between different countries on energy efficiency. Meanwhile, influencing factors like governmental policies, technological innovation is also discussed (Li & Lin, 2015; Du et al.,2020; Zhang and Zhou,2020). In terms of the methods adopted by 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.

With regard to the DEA models from the literature very limited amount of research has applied the DEA model to address the issue of multiplicate activities in the efficiency analysis. An MNDEA model is used by Yu and Lin (2008) to analyse the efficiency level of the railway industry, and consumption and production are separated in the model. Wanke et al. (2018) use a super- efficiency MNDEA model with undesirable outputs to investigate drivers of railway performance. Ouyang & Yang (2020) point out that the traditional DEA model assumes that variables are independent, but variables in energy productions chain need to collaborate with each other to produce the outputs, and the multi-activity network DEA model would be able to find out which activity is the main source of (in)efficiency in the production process.

Previous research does not analyse energy efficiency in the energy production chain in China. For influencing factors, they consider more about technology and economics factors rather than deeper geographical factors. In this article, for analysing the efficiency in the Chinese energy production chain, several drivers such as fixed/variable productive cost ratios, raw fuel pre-processing, alternative uses for industry and heating, and its overall impact in terms of pollutant emissions would be taken into consideration. Meanwhile, numbers of demographical factors are taken into account to analyse their relationship with energy efficiency.

Table 1. Synthesized table of previous research.

No.	Authors	Study Location	Year Published	Sample size	Time Period	Methodology	Major Conclusions	Application Scheme
1	Li and Hu,2012	China	2012	30 regions	2005-2009	SBM-DEA	On the whole, China's regional ETFEE (Eco Total Factor Energy Efficiency) was low, and the extreme regional energy efficiency unblance exists. R&D investment and level of dependence on foreign investment has positive relationship with regional energy efficiency.	regional ecological total-factor energy efficiency
2	Jia & Liu, 2012	China	2012	30 provinces	2004-2010	DEA model+Tobit model	Beijing and coastal southern cities have higher energy efficiency than middle and western areas;Gross Domestic Product (GDP) per capita, the proportion of tertiary industry and the urbanization rate were found to be the key elements that affect energy/environment efficiency	the dynamic characteristics of energy and environment efficiency andthe factors affecting efficiency
3	Goto et al., 2014	International	2014	47 prefectures in Japan	2002-2008	DEA model	environmental regulation benefits the performance of Japanese industries; the emission of greenhouse gases is a main source of unified inefficiency in the two groups of industries	unified (operational and environmental) efficiencies assessment
4	Huang et al., 2014	China	2014	30 regions	2000-2010	GB-US-SBM	The average eco-efficiency displays a V shape and the bottom is in 2005. large gap between eastern, middle and western areas in China for the regional efficiency	regional efficiency

5	Li & Lin, 2015	China	2015	29 provinces	1996-2012	Combination of super-efficiency and sequential DEA models	China's improvement energy intensity fluctuates around 21%, 7.5% and 12% for Eastern, Central and Western China respectively; and Eastern China has the highest level of energy technology	regional energy intensity
6	Liu & Wang, 2015	China	2015	30 provinces	2008-2014	Network DEA model +Adjusted efficiency decomposition approach	an adjusted energy efficiency evaluation model that can characterize the inner structure and associated energy utilization properties of the industry sector so as to avoid evaluation bias	China's provincial industrial energy efficiency
7	Jebali et al.,2017	International	2017	24 countries	2009-2012	two-stage double bootstrap DEA	energy efficiency levels in the Mediterranean countries are high and declining over time. The results of the second stage analysis reveal that the gross national income per capita, the population density, and the renewable energy use impact energy efficiency	the energy efficiency determinants
8	Iftikhar et al., 2017	International	2017	19 major economies	2015	Network DEA	Economic and distributive inefficiencies brought more than 80% energy consumption and CO_2 emissions. China skewed on economic inefficiency, and US skewed on distributive inefficiency.	energy and CO_2 emissions efficiency of economies in terms of economic and distributive efficiencies

9	Zhou et al.,2019	China	2019	38 industries	2010-2014	New DEA model (using an exponential transformation)	most sectors in Chinese industry have not performed well, especially the sectors concerned with energy extraction	the energy efficiency of Chinese industry
10	Yu et al.,2019	China	2019	30 regions	2006-2016	Meta-Frontier Method+SBM	decoupling relationships between energy consumption and economic growth is displayed in provinces; eastern areas have a higher level of energy efficiency. state intervention and market openness had negative impacts on energy efficiency in different study periods.	regional heterogeneity of China's energy efficiency
11	Wang et al.,2019	International	2019	25 countries	2008-2017	GM (the grey method) and SBM-DEA	European countries have a higher energy efficiency, and the excess of energy consumption is the reason for the energy inefficiency	Measure energy efficiency
12	Zhao et al.,2019	China	2019	30 provinces	2008-2016	Three-Stage DEA	the provincial energy efficiencies in China are significantly affected by economic and energy consumption structure, urbanization process, and technical innovation level.	China's provincial energy efficiency

13	Du et al.,2020	China	2019	30 provinces	2009-2016	Two-stage network DEA	The green innovation efficiency of Chinese industrial enterprises shows significant regional imbalances and differences has positive relationships with energy efficiency.	the efficiency of industrial enterprises' green technology innovation and explore their regional differences
14	Sun et al.,2019	International	2019	71 developed and developing countries	1990-2014	Parametric stochastic frontier approach based on the shepherd distance function	positive influence of both green innovation and institutional quality on energy efficiency enhancement	energy efficiency performance
15	Chen et al., 2020	China	2020	30 regions	2000-2012	multiplicative relational network DEA model+window analysis	significant heterogeneity among provinces for environmental sustainability and eco-efficiency indices , unbalance production efficiency in China	regional efficiency
16	Zhang and Zhou,2020	China	2020	284 cities	2003-2013	the Shephard energy distance function + the "double" stochastic meta-frontier	the regional heterogeneity has significant impact on the energy efficiency; the energy efficiency of cities and gaps vary under different group criterion, which highlights the importance of specified criterion and technology heterogeneity.	measuring energy efficiency inequality

17	Cheng et al.,2020	China	2020	30 provinces	1997-2016	DEA+Meta-frontier method	total-factor energy efficiency has significant regional heterogeneity, with the largest in the Eastern region, the second in the Central region and the smallest in the Western region. The root cause of energy inefficiency in China is poor management.	the spatial convergence of energy efficiency and explore the reasons for regional differences in energy efficiency
18	Qi et al.,2020	China	2020	14 major Chinese coal-intensive industries	2006-2015	Super Efficiency Model of DEA	total-factor energy efficiency of coal consumption overall showed a trend of growth from 2006 to 2015, technology innovation has important impact on the energy efficiency.	measured the energy efficiency by using coal consumption and reasons behind
19	Ouyang and Yang,2020	International	2020	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. On the other hand, the networked analytical structure can give policymakers more detailed analysis results than single process method.	regional energy and environmental efficiency
20	Shang et al.,2020	China	2020	Thirty provinces and municipalities	2005-2016	SBM-DEA	high TFEE value in certain area could promote the value of surrounding provinces, indicating that China's current economic growth is still dominated by energy consumption, and China is also in the middle and late stages of industrialization.	considering undesired generations to measure the total factor energy efficiency in different regions of China

3. Methodology

In this part, the methodology would explain two-stage approach. Section 3.1 would analyze the DEA model; In the 3.2, data of the research would be explained; section 3.3 would depict model of the research in detail.

3.1 The DEA model

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

The seminal MDEA model was originally presented in Beasley (1995). Mar Molinero (1996) further revised the model into linear form with a Shephard's distance function. Departing from Tsai and Mar Molinero (1998, 2002)'s modelling, the traditional DEA is modified here to a multi-activity network model by permitting the productive structure to be formed by a number of processes organized in series (cf. Fig 1). These processes characterize the productive network structure. It is possible to compute an overall efficiency score of all these processes by multiplying their respective individual efficiency scores. Each process can be formed by a number of different stages or activities in parallel, which are allowed to grade their performance independently under their own technology frontier, although they may share some inputs and their outputs may contribute subsequently to the next process. The efficiency scores for each process are obtained as an additive weighted average of the efficiency scores computed for each activity or stage. Put into other words, while overall efficiency scores are computed in an additive fashion at the activity level, overall efficiency scores at the process level observe a multiplicative fashion.

Let's consider a simpler case, with only one process formed by several activities or stages. More specifically, let's suppose that there are k $(k = 1, \ldots, K)$ DMUs and that each one is enrolled in I activities or stages. Let $X_k^1, X_k^2, \ldots, X_k^I$ and $X_k^s = (x_{k,1}^s, x_{k,2}^s, \ldots, x_{k,L}^s)$ denote the inputs and the respective shares of DMU k. X_k^i is the input vector linked exclusively with the ith activity, while $x_{k,l}^s$ is the lth input that is shared by the I activities. Due to the fact that $x_{k,l}^s$ is a shared input, it is considered that some fraction $\mu_{k,l}^i \left(0 < \mu_{k,l}^i < 1, \sum_{i=1}^I \mu_{k,l}^i = 1\right)$ of it is allocated to the ith activity. In this multi-activity structure, $\mu_{k,l}^i$ represents a decision variable to be computed for each DMU. Therefore, 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 $\mu_k^i X_k^s = (\mu_{k,1}^i x_{k,1}^s, \mu_{k,2}^i x_{k,2}^s, \ldots, \mu_{k,L}^i x_{k,L}^s)$, $Y_k^i = (y_{k,1}^i, y_{k,2}^i, \ldots, y_{k,M_i}^i)$ and $B_k^i = (b_{k,1}^i, b_{k,2}^i, \ldots, b_{k,R_i}^i)$. This notation for only one process can be easily modified-by incorporating an additional index-to represent a network structure composed by K process.

Hence, the MNDEA scores for DMUs are calculated as the solution for the following nonlinear programming problem, as given next:

$$\begin{aligned}
&Max \qquad \rho^{j'} = \prod_{k=1}^K \sum_{i=1}^I w^{k,i}\, \rho_{j'}^{k,i} \\
&\quad s.t. \\
&\quad \sum_{j=1}^J \lambda_j^{k,i}\, Y_{j,m_i}^{k,i} \geq \left(1+\rho_{j'}^{k,i}\right) Y_{j',m_i}^{k,i} && \forall k, \quad \forall i, \quad \forall m_i \\
&\quad \sum_{j=1}^J \lambda_j^{k,i}\, B_{j,r_i}^{k,i} = \left(1-\rho_{j'}^{k,i}\right) B_{j',r_i}^{k,i} && \forall k, \quad \forall i, \quad \forall r_i \\
&\quad \sum_{j=1}^J \lambda_j^{k,i}\, x_{j,l_i}^{k,i} \leq \left(1-\rho_{j'}^{k,i}\right) x_{j',l_i}^{k,i} && \forall k, \quad \forall i, \quad \forall l_i \\
&\sum_{i=1}^I \sum_{j=1}^J \lambda_j^{k,i}\, \mu_{j',s}^{k,i}\, x_{j,s}^{k,s} \leq \sum_{i=1}^I \left(1-\rho_{j'}^{k,i}\right) \mu_{j',s}^{k,i}\, x_{j',s}^{k,s} && \forall k, \quad \forall s \quad (4) \\
&\sum_{i=1}^I \mu_{j',s}^{k,i} = 1 && \forall k, \quad \forall s \\
&\sum_{j=1}^J \lambda_j^{k,i} = 1 && \forall k, \quad \forall i \\
&\lambda_j^{k,i} \geq \varepsilon && \forall k, \quad \forall i, \quad \forall j \\
&0.3 \leq \mu_{j',s}^{k,i} \leq 0.7
\end{aligned}$$

$\rho_{j'}^{k,i} \geq 0$

Where:

$\rho_{j'}^{k,i}$ is the stage i technical inefficiency of DMU j' in process k

$w^{k,i}$ is the weight set to stage i in process k

$\mu_{j',l}^{k,i}$ is the allocation of shared input l in stage i of DMU j' in process k

i is the number of stages present in process k

s is the number of shared inputs in process k

l_i is the number of inputs of stage i in process k

m_i is the number of desirable outputs of stage i in process k

r_i is the number of undesirable outputs of stage i in process k

As Yu and Lin (2008) indicated, we restricted the $\mu_{j',l}^{k,i}$ to lie within the range from 0.3 to 0.7. These values are a common sense practice of shared input allocation for railways. The MNDEA model evaluates the process technical inefficiency of DMU by a weighted mean of each DMU stage technical inefficiency as follow:

$$TIE_{j'}^{k} = \rho^{k,j'} = \sum_{i=1}^{I} w^{k,i} \rho_{j'}^{k,i} \tag{5}$$

The weight $w^{k,i}$ is the positive value that gives the relative importance attributed to the activity or stage i in process k . Their summation is standardized to be equal to 1 in each process k. The overall technical inefficiency of DMU j' is the product of each process technical inefficiency:

$$TIE_{j'} = \rho^{j'} = \prod_{k=1}^{K} TIE_{j'}^{k} \tag{6}$$

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

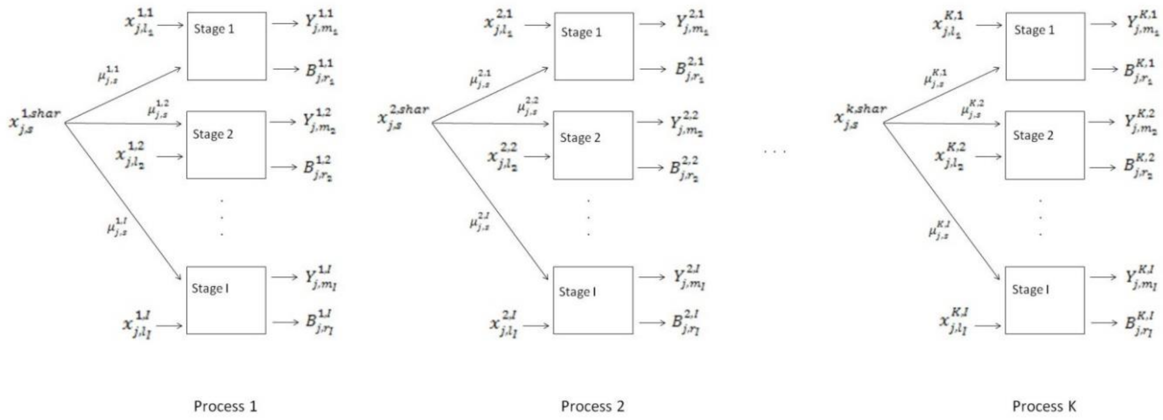
$$TE_{j'}^{k} = 1 - \rho^{k,j'} \tag{7}$$

And we can extend to overall technical efficiency:

$$TE_{j'} = 1 - \rho^{j'} \tag{8}$$

Model (4) observes VRS assumption. CRS assumption is obtained by removing $\sum_{j=1}^{J} \lambda_j^{k,i} = 1, \forall k, \forall i$ from model (4).

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



3.2. The Data of the research

All direct and indirect data comes from National Bureau of Statistics of China. In the first stage, The time span is used from 2009 to 2016. 16 variables including CAPEX (capital expenditure), OPEX (operating expenditure), etc. are used in the MNDEA model as Table 2 shows below. We evaluate all variables through R programming tools (R Core Team, 2020).

Table 2 listed all variables in the energy production chain. They are input variables, and the output variables are intermediate phases. In the Figure 2, the research describes the energy production chain through 4 intermediate phases. Through different phases, we can compute and evaluate energy efficiency in the energy production chain. The time period cross three Five-Year plans in China. Therefore, the paper can evaluate the trend based on the country's energy management policies. The period during 2009 to 2010 is the last two years of the Eleventh Five-Year Plan; The period during 2011-2015 is the whole process of the Twelveth Five-Year Plan, and 2016 is the first year of the Thirteenth Five-Year Plan. From the data, we can see the whole country and different provinces' heterogeneity and homogeneity.

Table 2. Descriptive Statistics for MNDEA variables.

Variable	Unit	Min	Max	Mean	SD	CV
CAPEX	100 million yuan	798.23	53322.94	13590.27	9880.81	0.73
OPEX	100 million yuan	253.91	77523.27	14881.32	14161.39	0.95
Coal	10000 ton	536.89	40939.20	13801.76	10034.04	0.73
Coke	10000 ton	0.02	8402.28	1303.61	1534.13	1.18
Crude Oil	10000 ton	0.00	10203.42	1608.69	1782.89	1.11
Diesel	10000 ton	87.11	1814.34	578.56	344.28	0.60
Kerosene	10000 ton	0.01	594.27	77.81	118.17	1.52
Fuel Oil	10000 ton	0.03	4511.42	172.94	456.66	2.64
Gasoline	10000 ton	20.04	1502.44	379.56	277.69	0.73
Natural Gas	10000 ton	9.68	1452.56	413.68	332.52	0.80
LPG	10000 ton	0.54	505.60	37.87	72.41	1.91
Hydro	100 million kWh	0.00	2854.42	293.83	491.52	1.67
Value Added	100 million yuan	300.63	32650.89	8052.73	6833.93	0.85
Hot Water	MW	20.00	74997.45	23620.06	17774.67	0.75
Steam	10000 ton	22.78	27231.34	4228.97	4362.29	1.03
CO2	10000 ton	1177.00	43467.74	11422.43	7655.51	0.67

In the second stage, through neural networks, contextual variables were taken into account to analyze demographical factors’ influence on the sustainability of the energy production chain. These factors, involving fields like environment, population, education, economy, health, travel, are depicted in Table 3. After the evaluation of energy efficiency, the relationship between following contextual variables and energy efficiency can be analyzed.

Table 3. Descriptive Statistics for demographical variables.

Variable	Unit	Min	Max	Mean	SD	CV
Cleaning Area	10000 m²	1807	132135	20690.03	18600.73	0.90
Birth Rate	Births/1000 Persons	5.36	17.89	11.23	2.62	0.23
City Illiteracy	%	1.46	15.94	5.52	3.00	0.54
CPI	%	-2.30	6.30	2.41	1.69	0.70
Death Rate	Deaths/1000 Persons	4.21	7.24	5.98	0.75	0.12
City Employed	%	13.94	42.10	22.14	5.06	0.23
Exchange in Tourism	USD Million	4.43	18577.13	2063.74	3009.10	1.46
Garbage Disposal	10000 tons	66.25	2390.95	580.84	421.90	0.73
GDP PPP	yuan/Person	10971	118198	44691.11	22424.13	0.50
GDP	100 Million yuan	1081.27	80854.91	19648.76	15597.79	0.79
GINI Index	-	0.46	0.49	0.47	0.01	0.02
Health Care Institutions	Unit	4129	81403	31794.11	21571.57	0.68
Students in Higher Education	Students/100000 Persons	1043	6410	2471.75	889.61	0.36

Students in Jr. Secondary	Students/100000 Persons	1236	6146	3490.60	1007.08	0.29
Students in Primary Education	Students/100000 Persons	3175	12046	7097.48	2013.18	0.28
Students in Sr. Secondary	Students/100000 Persons	1120	4931	3231.67	739.55	0.23
Students in Kindergartens	Students/100000 Persons	1110	4371	2610.97	746.72	0.29
Passengers in Highways	%	23.60	97.26	86.96	12.45	0.14
Passengers in Railways	%	0.17	73.60	11.83	11.84	1.00
Passengers in Waterways	%	0.00	14.78	1.21	1.91	1.58
Passengers Total	10000 Persons	4790	574266	89356.80	81572.42	0.91
Civil Vehicles	10000 Vehicles	24.35	1723.34	401.24	330.66	0.82
Passenger Vehicles	%	63.76	94.67	80.53	6.75	0.08
Resident Population	10000 Persons	557	10999	4495.84	2691.37	0.60
Urban Population	%	29.88	89.61	54.76	13.09	0.24
City Unemployed	%	0.40	2.10	1.14	0.36	0.32

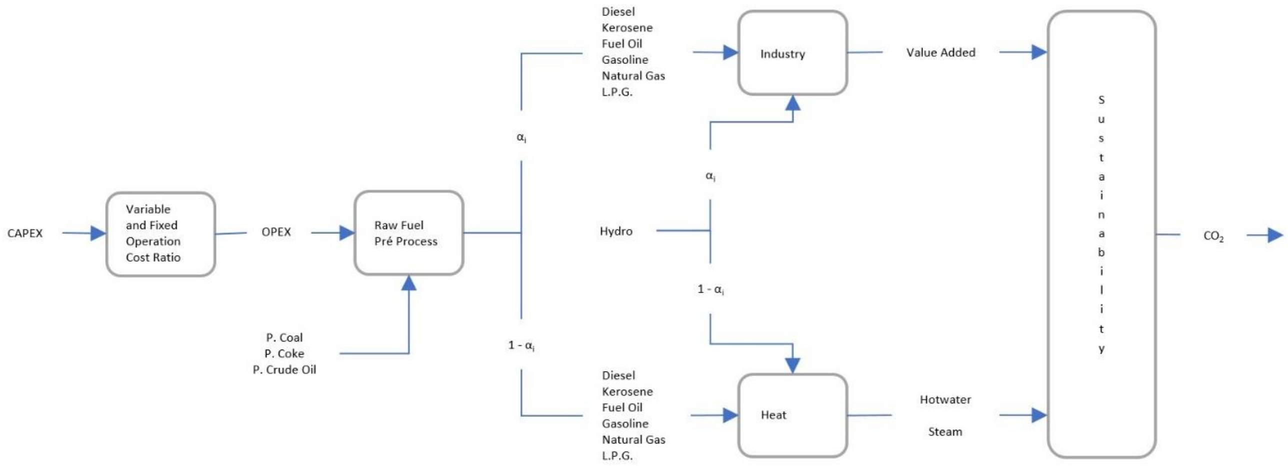
3.3 The model of research

Previous literature has conclusions about relationships between parts of following contextual variables. Li and Hu (2012) point out 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-process, since education would have an impact on technology and people’s awareness about energy efficiency. For industry and raw fuel pre-process, its development also depends on capital investment and technology development. Jia and Liu (2012) find that Beijing and 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, urbanization level of provinces.

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

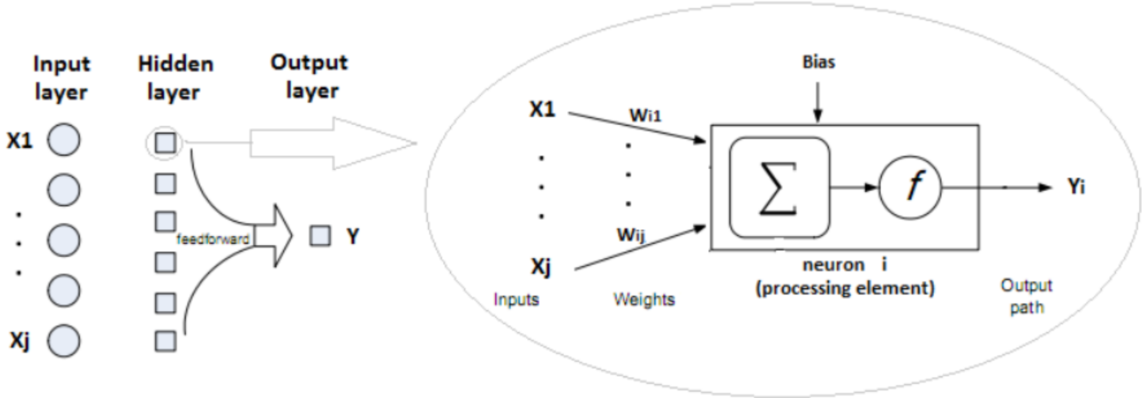
In the study, we use a hybrid neural-MNDEA model. First, we map the Chinese sustainability model as the figure 2 shows. In the first stage, through MNDEA model, the energy production chain in China would be divided into four processes. In each part, the energy efficiency would be evaluated. From CAPEX to OPEX, the energy efficiency in the variable and fixed operation ratio is considered. Then adding the coal, coke and crude oil, energy efficiency in raw fuel pre- process is considered. After processing, all fuels are entered into industry and heat sectors through general energy we use in our production and lives, like diesel, kerosene, fuel oil, gasoline, L.P.G. and hydro. Then through added value and hot water steam, the 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 also would 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 time trend are computed and evaluated. All 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.

Figure 2. Chinese Sustainability model



Second, after the first stage MNDEA efficiency assessment on the Chinese energy production chain, the second stage focusses on the relationships between contextual variables and the overall efficiency levels. These relationships are explored by means of ANNs (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 amongst the most used in forecasting applications (Mubiru and Banda, 2008). A typical MLP is given in Fig. 3.

Figure 3. Example of an MLP (left) and details of a neuron from the hidden layer (right)

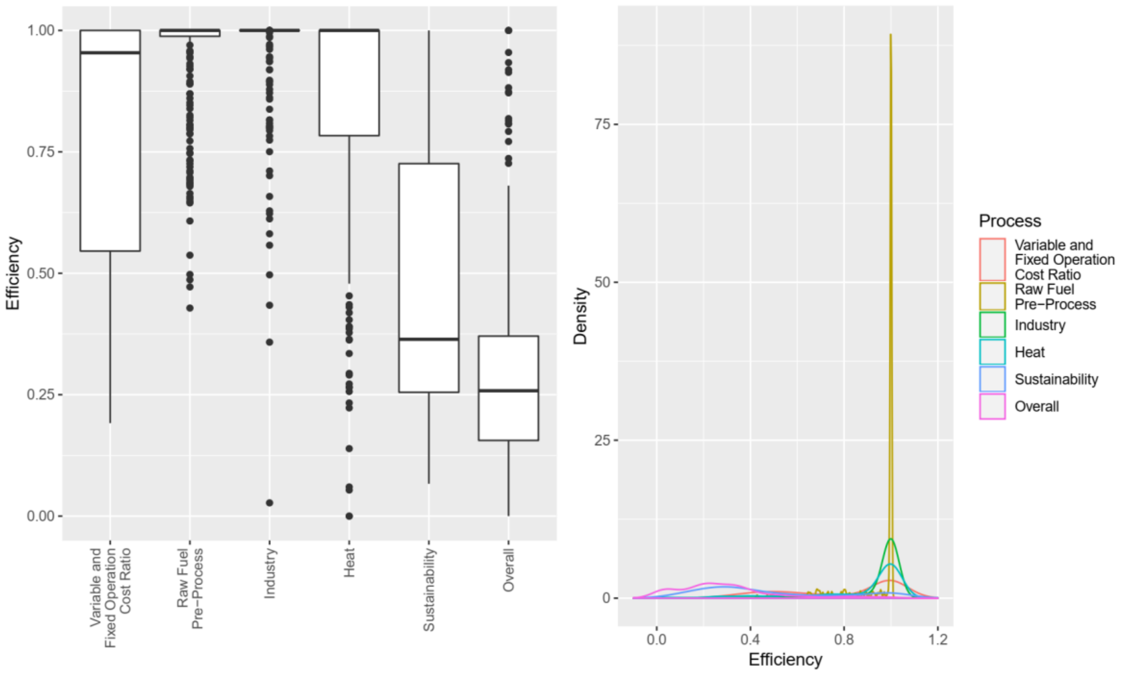


Precisely, the Connection Weight Approach (CWA) described in Olden et al. (2004) and Olden and Jackson (2002) is used to assess the relative importance of each contextual variable on the overall efficiency level of the Chinese energy production chain. This approach accurately identifies the true importance 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 2009-2016, three aspects have been analysed. First, through Figure 4, Figure 5, and Figure 6, the overall energy efficiency in the energy production chain in China, efficiencies of each process by year and the situations in different provinces, respectively. Second, through Figure 7, Figure 8, and Figure 9, optimal industry share of energy sources by country, by the time trend and by provinces have been analysed, respectively. Third, Figure 10 has showed the result of contextual variables which have influence on the energy efficiency of energy production chain.

Figure 4. Energy efficiencies for each process (left: boxplot; right: density plot)



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 the CAPEX (Capital expenditure) to OPEX (Operation expenditure), variable and fixed operation cost ratios are calculated. Before all energy are applied to the industry and heat, raw fuel pre-process is evaluated. After its application, sustainability is used to evaluate how much CO_2 is released. The country's energy efficiencies of different processes have been showed 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 mean of overall energy efficiency score in the boxplot is around 0.25, which is the lower than all the other phases. looking at the mean values of different phases, raw fuel pre-processes and industry process are close to 1, displaying a relative high level of energy efficiency. However, these two phases have numbers of outliers comparing to other phases. The raw fuel pre-processing shows the highest level of density in the density plot, exceeding 75%. The distribution of energy efficiency of other phases disperses. Meanwhile, other phases' density is less than 25%. After the value-add process from industry and heat, the mean, the max and the minimum scores of the sustainability phase are lower than 0.75, and the minimum line is close to 0.25, which means that in the end of the energy production chain, it still displays with the lower position of the overall energy efficiency, Chinese overall energy efficiency and level of sustainability is low. Our results are in contrast with Zhao and Hu (2020) who report higher level of energy efficiency compared to us. The main difference is attributed by 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 National Bureau of Statistics. This comparison also shed the 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 have lots of space to improve, in particular for the final phase. From the energy production chain, the data depicts that from the value-add process in the industry and heat to the CO_2, current working flow cannot work sustainable.

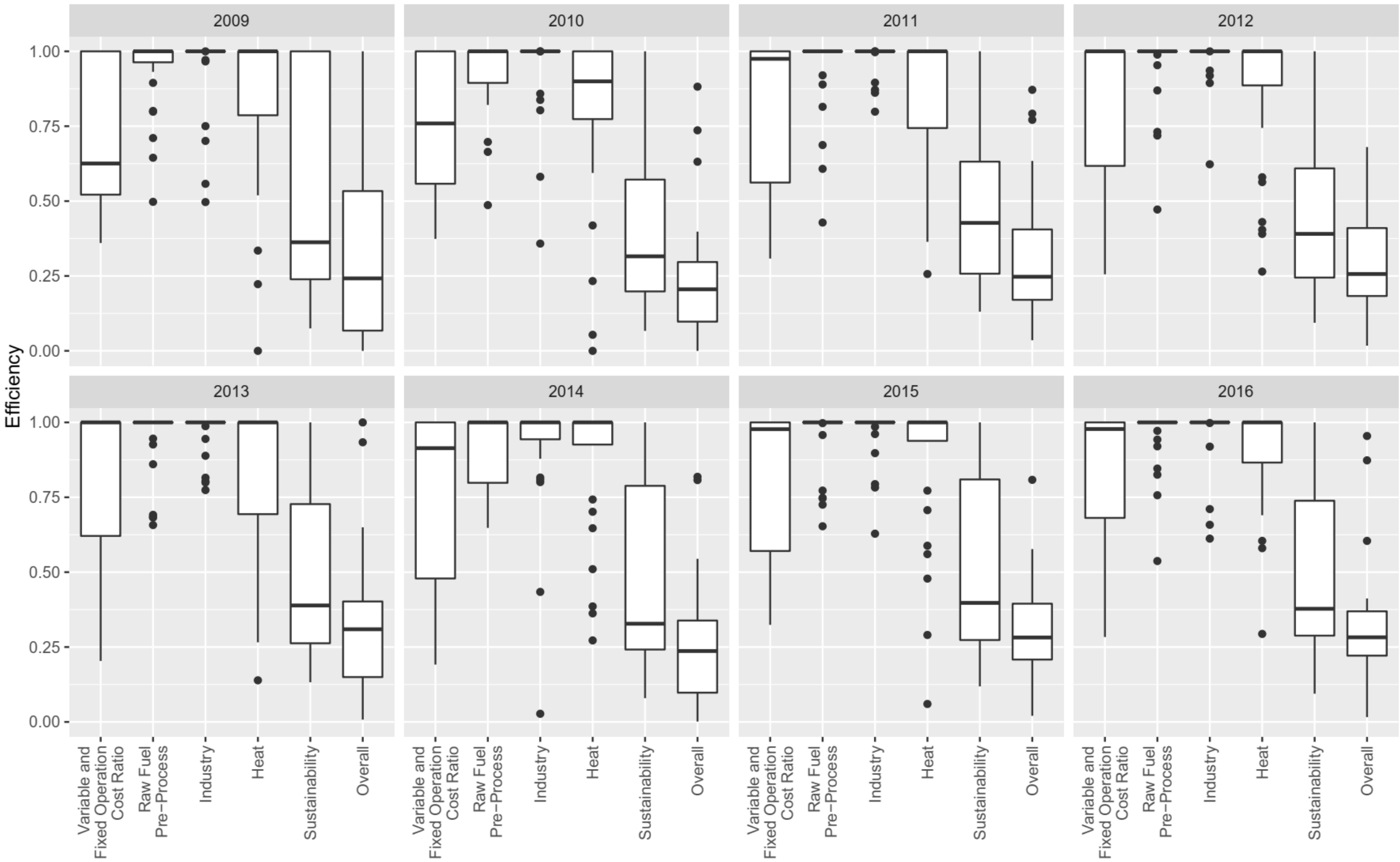


Figure 5. – Boxplot of efficiencies for each process by year.

4.1.2 The time trend of energy production chain

Figure 5 depicts the boxplot of energy efficiencies for each process by year. From 2009 to 2016, the energy consumption policies go from the last two years of the eleventh five-year plan to the whole twelfth five-year plan, and then the year 2016 is the beginning year of the thirteenth five- year plan. From 2009 to 2016, China has progressed so much economically, and also increased its energy consumption. Based on the country's five-year plan, China has established different policies related to energy and environment. From the eleventh five-year plan to the thirteenth five-year plan, it emphasizes more on clean energy and environmental protection, which would be better for the sustainability of the energy consumption and improve the economic competitiveness. The inter-quartile range of the overall energy efficiency becomes narrower during 2009-2016. Although the mean of the boxplot keeps constant around 0.25, the lower quartile keeps increasing gradually. In 2009, the lower quartile closes to 0, but in 2016, it closes to 0.25. Combining Figure 4 and Figure 5, two figures depict that the overall energy efficiency in China is low, but the situation becomes better year by year. It means that the Chinese five-year plan related to energy development has a good influence on the energy production chain, but it still has a large room to improve. The positive influence of five-year plans on energy efficiency is supported by Zhu et al. (2020). The sustainability phase keeps at a low level in the energy efficiency, and the boxplot is taller than other phases during 2009-2016, showing bigger differences among provinces. Raw material pre-process and industry phase keep a high-level energy efficacy, closing to 1 in most of years. For the beginning phase, variable and fixed operation cost ratio, the mean is low in the first two years, but since entering into the twelfth five-year plan, the phase improves significantly and keeps at a higher level of energy efficiency.

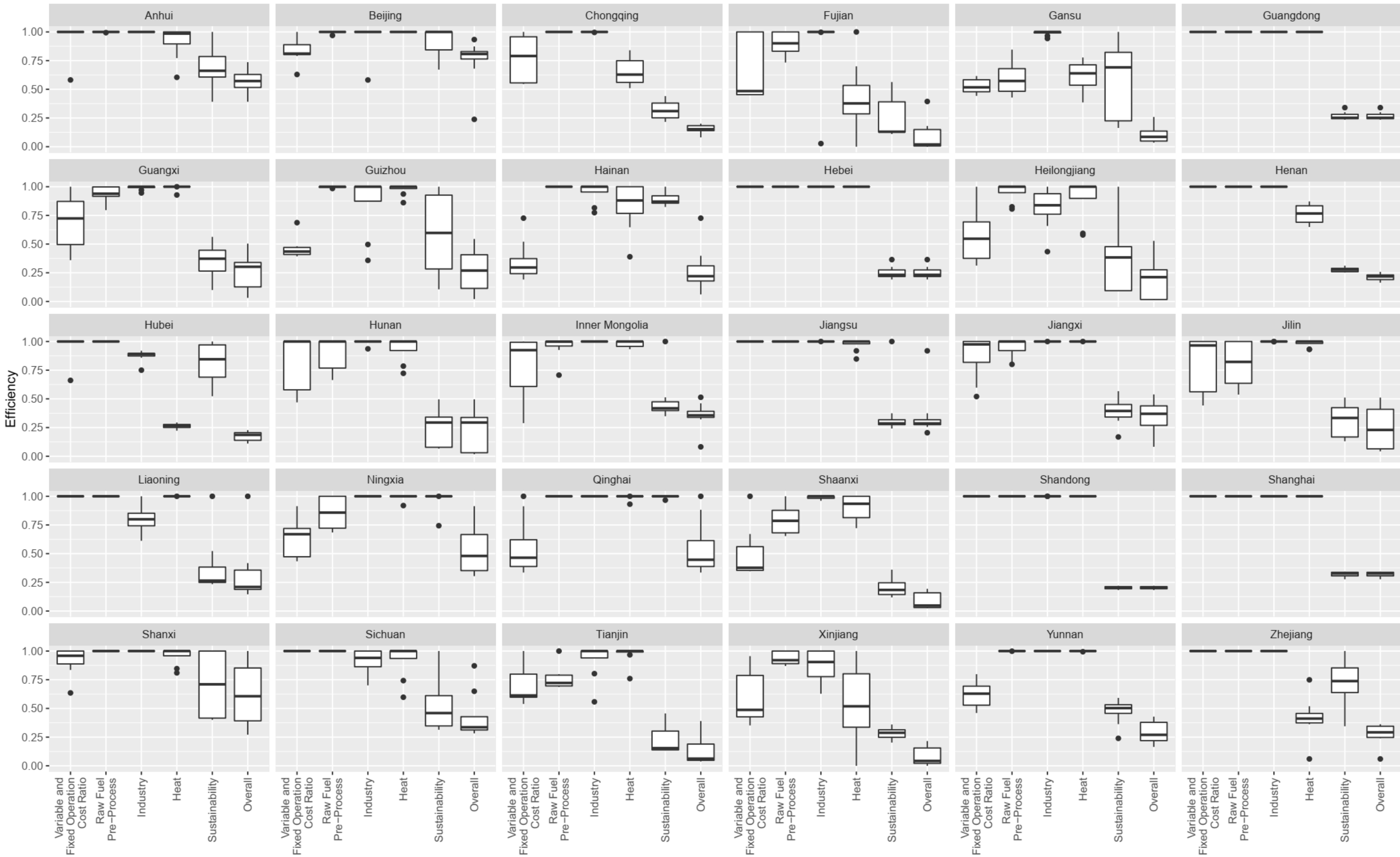


Figure 6. – Boxplot of efficiencies for each process by provinces

4.1.3 Energy efficiencies by provinces

Figure 6 shows the boxplot of efficiencies for each process by provinces. 30 capital cities of provinces show their interpreted results of energy efficiency in different phases in the energy production chains. Different provinces have different natural resources, industry features and geographical features, so there are different characteristics in the phases of the energy production chain among them. For most of the cities, the sustainability score is consistent with the overall energy efficiency score. It means that if the provinces have higher levels of sustainability and less 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 less pollutants at the end of the energy production chain. Therefore, its sustainability and overall energy efficiency are better than other cities. Anhui, located in 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 past years to attract lots of high technology industries. our results show that the eastern area in China has higher ETFEE (Eco Total Factor Energy Efficiency) than the Central and Western areas. this finding is in line with Li and Hu (2012) as well as Cheng et al., (2020). . Provinces in all three areas all have good scores and bad scores. Most cities have low scores on the sustainability and the overall energy efficiency scores. Eastern areas including Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Shandong, Guangdong have higher energy efficiency than the middle, north-eastern and western areas such as Heilongjiang, Guizhou, Xinjiang, Ningxia. 10 of 30 capital cities have tall boxplot (bigger than 0.25) on the variable and fixed operation cost ratio, showing low energy production transformation, which would deteriorate energy efficiency.

4.2 Optimal energy efficiency

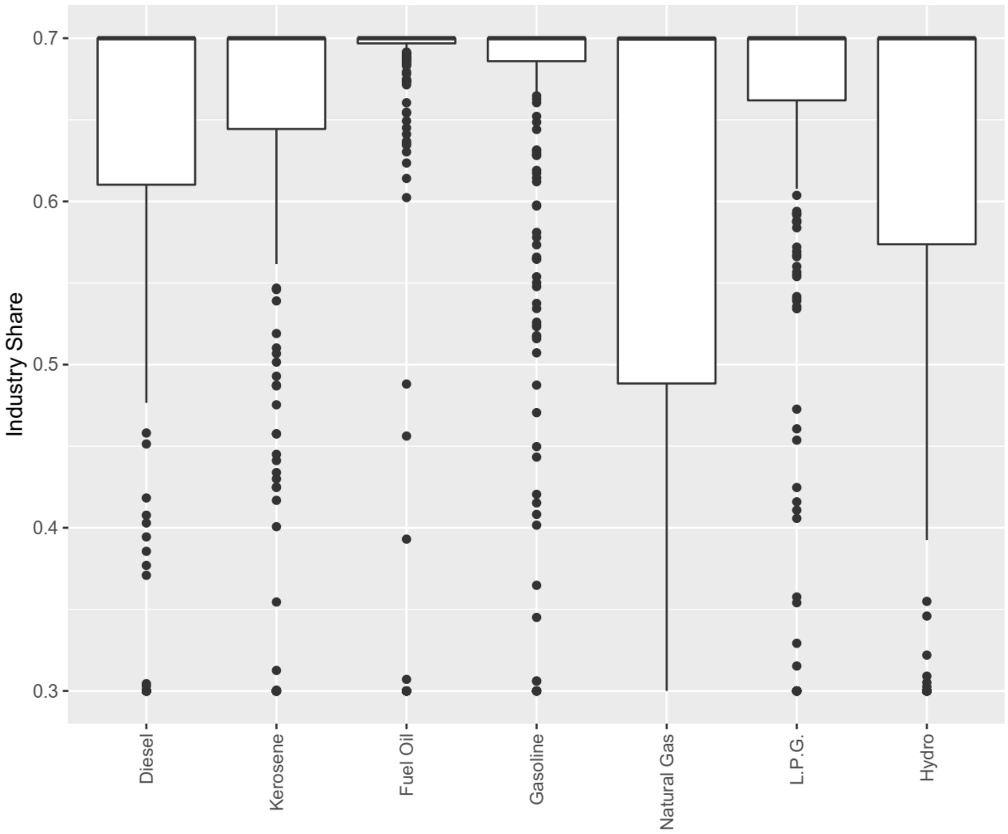


Figure 7. – Boxplot of Optimal Industry Share of energy sources

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 natural gas has the tallest interquartile. Except the natural gas, all other sources have a number of outliers. Figure 4 indicates that the country relies heavily on fuel oil, and in terms of natural gas, which is the clean energy, it has an unbalanced distribution in China. However, natural gas would be beneficial for the sustainability of the environment and the economy as a clean energy, so the distribution of industry share still has a room for improvement.

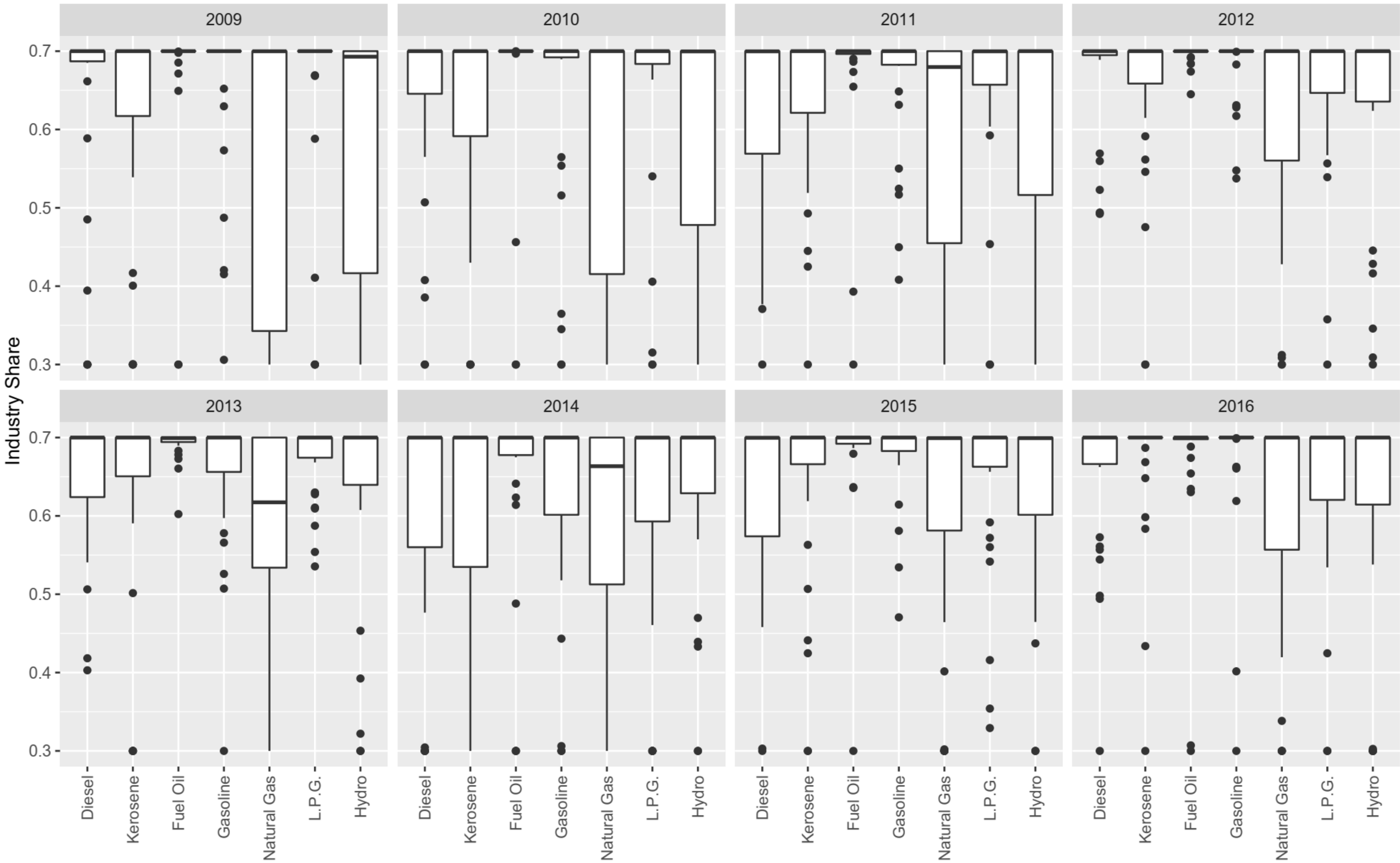


Figure 8. – Boxplot of Optimal Industry Share of energy source by year

4.2.2 The time trend of optimal industry share of energy sources

The time trend of optimal industry share of energy source is depicted in figure 8. Fuel Oil and Natural Gas are in the two-end point among the industry. These two sources display the same trend with the country's overall trend over the period. From the last two years of eleventh five-year plan period to the end of twelfth five-year plan, the interquartile of natural gas becomes shorter, and concentrates from 0.5-0.7, which means that the country uses more natural gas and develops their energy strategy towards a positive direction. Hydro is also the clean energy. The time trend of Hydro displays a good performance with most of its lower quartile more than 0.6. For fuel oil, China relies on it the most among all energy sources during the past years. It indicates that China doesn't develop their clean energy sufficiently.

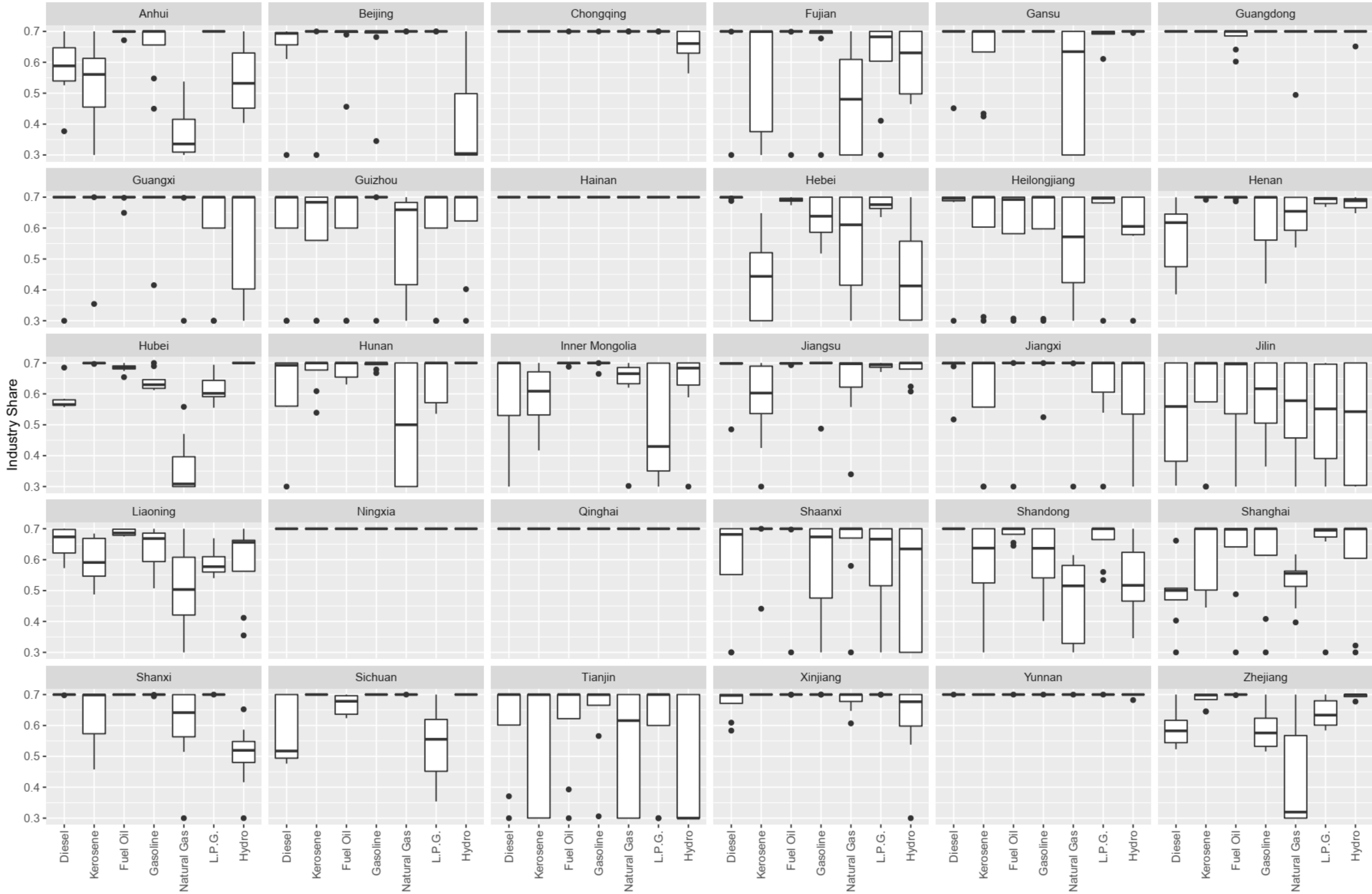


Figure 9. – Boxplot of Optimal Industry Share of energy sources by province

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. 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. Provinces such as Chongqing, Guangdong, Hainan, Ningxia, Qinghai, Xinjiang, 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 and Guangdong have good economic performances comparing to Hainan, Ningxia, 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 on the optimal industry share comparing to their energy efficiency. However, comparing between traditional energy and clean energy, almost all provinces rely more on traditional energy and still have a room to improve their optimal industry energy share. The whole distribution of optimal energy share is consistent with the trend of the overall sample.

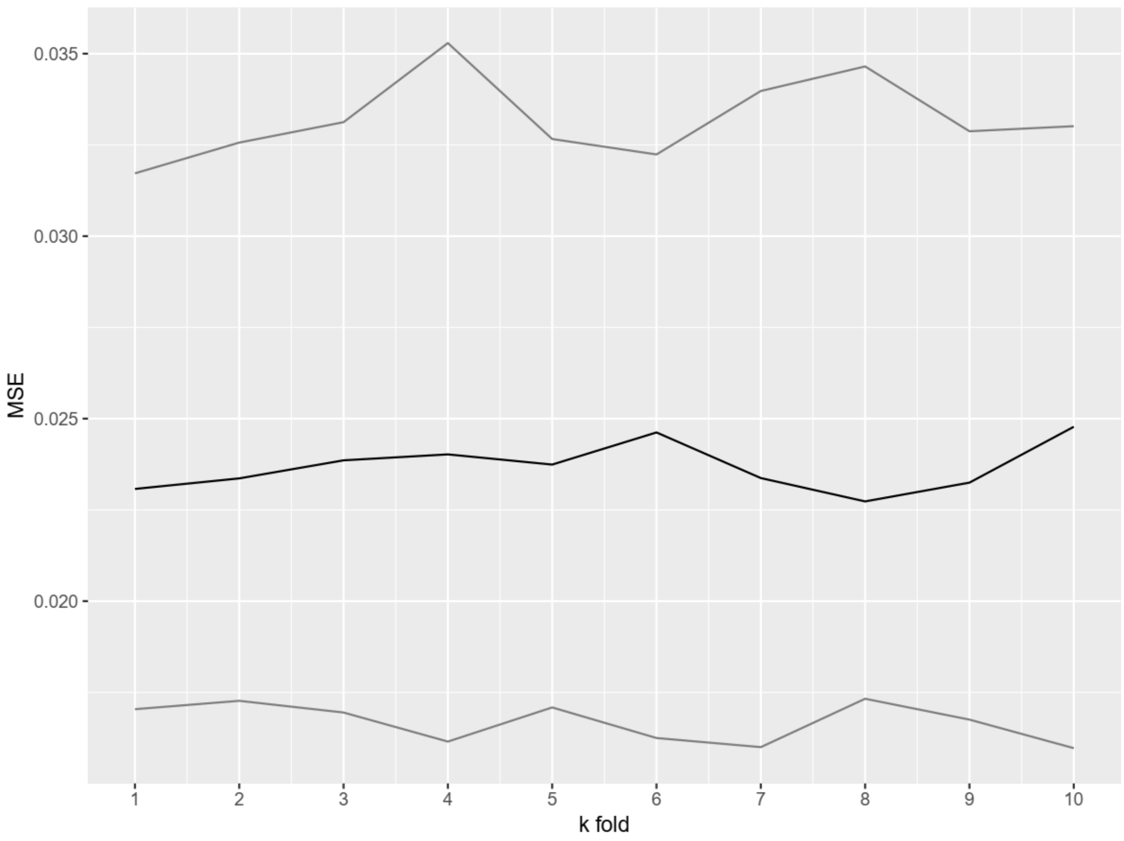


Figure 10. – Mean Squared Error of 10 fold cross validation test in 100 training repetitions (95% of confidence interval)

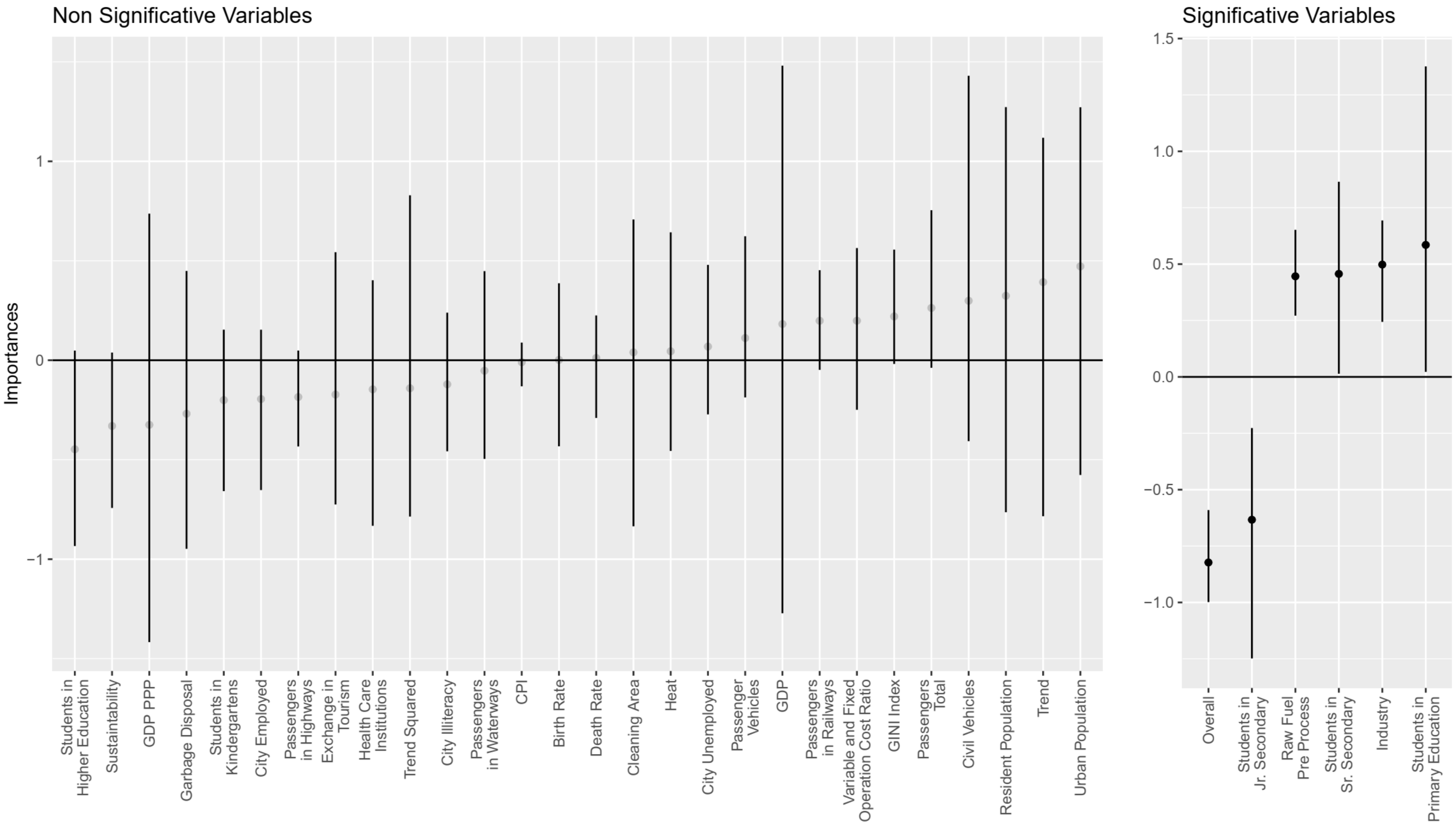


Figure 11. - Contextual Variables Importance (95% Confidence Interval)

4.3 Contextual variables importance related to energy efficiency

Figure 10 and Figure 11 depict the contextual variables' importance on the energy production chain. We consider comprehensive contextual variables that are used by previous studies, including GDP, birth rate, Gini Index, education related index. Numbers of Students in Junior Secondary has a negative relationship with energy efficiency. Raw fuel pre-process, students in Senior Secondary, industry, and students in primary education have a positive relationship with energy efficiency in the energy production chain. As shown previously, most of the provinces and China as a whole have a high score of energy efficiency on phases of raw fuel pre-process and industry. The result indicates that more capital and technology are invested in developing phases of raw fuel pre-process and industry, which results in a higher energy efficiency. The positive influence of investment on energy efficiency is in accordance to Haider and Mishra (2021). Numbers of students in primary education has a positive relationship with energy efficiency, which indicates the awareness towards energy production and consumption would be enhanced by promoting the primary education and increasing the proportion of younger people to get educated. Meanwhile, the number of senior secondary students also has a positive relationship with energy efficiency. Senior secondary education is the preparation stage for the higher education (university education) in China, this phase will equip the students with relevant academic knowledge and improve their understanding on the importance of energy sustainability. In addition, education will also promote technology enhancement and further improve energy efficiency.

5. Policy implications

5.1 Strategies for different phases on the energy production chain

According to section 5.1, the combination of location and time dynamics have revealed the overall and detailed energy efficiency. Seeing from the first stage of analysis of energy efficiency in the energy production chain, the overall energy efficiency in China is still at a low level comparing to other phases in the production chain. Sustainability and overall phases have consistency with each other which related more with the final pollution. In the beginning phase, variable and fixed cost ratios, keeps at a middle level, but needs to improve to reduce capital loss. Related parties emphasize on the energy production, value-add process and the final emissions, but lack the awareness to improve the capital loss on the variable and fixed cost which make it higher. The beginning phase in the energy production chain still has lots of space to improve.

In the raw fuel pre-process and industry phases, no matter locations and years, two phases have better energy efficiency than other phases. It can be indicated that in the energy production and consumption phases, related parties have invested technological innovation and capital to improve the energy efficiency here. However, provinces have heterogeneity here, and local governments needs to consider how to adjust their energy and environmental policies to improve the energy efficiency.

The sustainability and the overall phases have positive relationships, which reminds related parties to take energy efficiencies more seriously. During 2009-2016, the overall energy efficiency in China has slow but continuous progress, proving the right directions of energy development policies from the country's Five-Year plans. However, it remains at a low level, so government policies and regulations need to consider that the energy efficiency improvement will be a long-term process.

5.2 Energy selections and consumption distributions

Section 4.2 combines location and time to analyse the optimal industry share of energy sources. From figure 7,8, and 9, results reveal that China relies more on the traditional energy, like diesel, gasoline, and have unbalanced development of clean energy, like natural gas, hydro. From the time trend, China has tried to adjust its optimal industry share of energy sources, because the interquartile of clean energy on figure 7 becomes shorter. China still needs to insist its five-year plan to transform from reliance on traditional energy to clean energy, which would be benefit for the sustainability of energy management and environment.

5.3 Contextual variables importance related to the energy efficiency

From the second stage analysis, students' numbers of primary education and Sr. Secondary, raw fuel pre-process, and industry have positive relationships with energy efficiency.

Two different strategy should be used on the aspect of education. For the primary education, students would be inspired to have more awareness to the energy production and consumption, and cultivate their awareness of importance between energy and environment. Then for students in Sr. Secondary, they need to receive more education related to

The government needs to invest more on education which would have positive influence on populations' awareness to improve energy efficiency in their life the future work. Meanwhile, it can be indicated that the education has close relationship with technology innovation which would have effects on the transformation of traditional energy production and consumption to the renewable energy consumption and production.

6. Conclusions

For evaluating the energy efficiency in China, we map the energy production chain and evaluate the energy efficiency of separate and overall phases through a MNDEA model. Using data from 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 source under the same approach.

From the perspective of energy efficiency, our research period covers three five-year plan periods from 2009-2016. The Chinese government has the right direction for the energy management. Although the sustainability and the overall energy efficiency is not good for the phases of raw fuel pre-process and industry, the trend of the sustainability of energy efficiency is upward. The same for the overall situation of the optimal industry share on energy sources. From the perspective of provinces, almost all 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. However, there is a level of homogeneity among most of the provinces. with regard to the energy efficiency, most of the provinces have a better performance on phases of raw fuel pre- process, 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 more differences among the provinces in the sample. Overall, China is lack of sustainability in the energy production chain, and has an unbalance consumption of industry share on the energy source. However, during the research period, China has improved its energy efficiency gradually but still has a long way to go. Meanwhile, China also tries to transform its consumption from traditional energy to clean energy although the process is slow during the past years. Therefore, Chinese government still needs to insist its five-year plan since energy efficiency improvement and optimal industry share of energy sources transformation will be a long but efficient process.

The paper uses the neural science to evaluate the importance of numbers of contextual variables on energy efficiency. Different from previous research, we find that factors related to the economy have close relationships with energy efficiency. The result shows that education in primary school and senior high school, raw fuel pre-process and industry have positive relationships with energy efficiency. Raw fuel pre-process and industry are important phases on the energy production chain. Sustainability will be enhanced by a higher level of investment. Primary education would inspire children to have more awareness about energy and society development, and senior school education would encourage students to invest their intelligence to improve energy efficiency in the future. Chinese government needs to invest more to provide energy efficiency related education to students, which would be beneficial for energy development in the long term. Meanwhile, education also would strengthen the process of raw fuel pre-process and industry. Therefore, on the bottom perspective, education would be the fuel for improve energy efficiency in China. And on the top perspective, insisting on the five-year plan would be a long-term strategy.

7. Limitations

The research discussed the energy efficiency in the energy production chain, the optimal industry share of energy sources, and contextual variable importance through MNDEL model, olden method, and neural science. The research did not discuss contextual variables further connecting to different provinces. In the further study, different provinces contextual variables can be evaluated to consider the reason of every provinces’ difference on phases of energy efficiency.

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