Journal Pre-proof

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PII: S0140-9883(20)30048-7

DOI: https://doi.org/10.1016/j.eneco.2020.104709

Reference: ENEECO 104709

To appear in: *Energy Economics*

Received date: 4 July 2019

Revised date: 29 January 2020

Accepted date: 6 February 2020

# Allocation of coal de-capacity quota among provinces in China: A bi-level multi-objective combinatorial optimization approach

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## ABSTRACT

Coal de-capacity, or capacity cut, is an important part of China's energy transition. Formulating a quota allocation scheme for coal de-capacity is the key to realizing smooth exit of coal overcapacity. This study proposes a novel method of allocation of coal de-capacity quota among provinces, based on bi-level multi-objective combinatorial optimization. In this bi-level optimal allocation scheme (BOAS), the upper level is the central government and the lower level is the provincial governments. The results indicate that, because of the different costs of coal de-capacity in each province, the execution rate of each province for tasks assigned by the central government is quite different. Compared with the government allocation scheme (GAS) and the single-level optimal allocation scheme (SOAS), the growth rate of total factor productivity of the BOAS increases by 2.14% and 0.60%, respectively; the total de-capacity cost of BOAS has reduced 64 billion yuan and 19 billion yuan, respectively; and the environmental benefits of BOAS has increased 73 billion yuan and 71 billion yuan, respectively; the Gini coefficient of BOAS calculated by various indexes is less than 0.3, placing the scheme within the category of considerable or absolute fairness. In addition, the proposed allocation model truly reflects the complex dynamics of the game process of China's coal overcapacity governance system, and can provide a more effective decision-making reference for the Chinese government in formulating the allocation scheme of coal de-capacity.

**Keywords**: de-capacity; quota allocation; bi-level multi-objective combinatorial optimization; coal industry; China

**Jel classification:** Q41; Q48; L72

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# 1. Introduction

Coal accounts for more than 90% of China's fossil energy resources. It is the most stable, economic, and independent energy resource, and plays an irreplaceable role in ensuring a sustainable and stable economy in China. As a basic energy resource, the planning of coal production capacity is very important for the healthy development of the coal industry, and in maintaining national energy security (Tang et al., 2018). Since 2001, with the rapid development of China's economy and the increasing price of coal, a large amount of capital has been invested in the coal industry and cause overcapacity. Specifically, since 2013, due to multiple factors such as the slowdown of China's economic growth (Yang et al., 2018), the decrease in energy consumption (Tan and Lin, 2018), and the tightening of environmental constraints, the supply and demand in China's coal industry has become largely unbalanced, aggravating the problem of overcapacity (Wang et al., 2018a; Wang et al., 2019a). According to the estimates of the China Coal Industry Association, Chinas total coal production capacity in 2018 was about 5.7 billion tons, while the coal production was only around 3.7 billion tons. The capacity utilization rate is less than 67%, which is far below the reasonable range of 79%-83% (Zhang et al. 2018). The over-capacity issue is further alarming by the fact that there are still several large-scale projects under construction in the coal industry. The over-capacity causes many problems, such as decline of industry profits, price distortion, worsened environmental pollution, and so on (Yuan et al., 2016; Shi et al, 2018).

Allocation of de-capacity quota is a key policy issue. Given the serious impact of overcapacity on the sustainable development of the economy, many studies have investigated the measurement (Zhang et al., 2018), cause (Yuan et al., 2016; Yang et al., 2018), prevention mechanisms (Zhang et al., 2017) and countermeasures (Shi et al, 2019) of coal overcapacity. However, few studies have been conducted on how to achieve this. If we rely solely on the current imperfect market mechanism, we will face the problems of long cycles, challenging issues and high costs, therefore, we need to rely heavily on the central administrative capacity management measures (Yang et al., 2018). The Chinese government has formulated a series of policies and measures in recent years to eliminate excess capacity[1], *The 13th Five-Year Plan for the Development of Coal Industry* issued by the National Development and Reform Commission in 2016 sets the total target of cutting 800 million tons of coal production capacity by 2020. Through the joint efforts of various regions, relevant departments and enterprises, some excess capacity has been

[1] Examples of such policies issued by the State Council of China are: “the Notice on Suppressing Overcapacity in Some Industries and Guiding the Healthy Development of Industries through Repeated Construction” in 2009， and “the Guiding Opinions on Resolving Serious Overcapacity Contradictions’ in 2013.

eliminated, but the over-capacity problem remains unchanged. Possible reasons are as follows: on the one hand, the current de-capacity policy formulated by the central government has certain planning nature and egalitarianism, ignoring the heterogeneity of the provinces in terms of financial endurance, environmental carrying capacity, and industry competitiveness, which has weakened the de-capacity enthusiasm of some provinces to a certain extent; on the other hand, for one region, different de-capacity ways adopted by local government have significant differences in the performance of local enterprises and the livelihood impact of miners, which could affect the de-capacity enthusiasm of coal enterprises (Zhang et al., 2017; Shi et al., 2018). The existing administrative de-capacity policy needs to allocate quota along the hierarchy of governments until to enterprises. Even market instruments, such as a Capacity Permit Trading Scheme (Shi et al., 2019), are implemented to allow local factors to be customized, a core but unresolved problem is how the initial de-capacity quota is allocated. One question is how the central government formulates a fair and scientific de-capacity allocation plan that considers regional differences, and improve the willingness of local governments to perform de-capacity tasks. Another question is, for a specific region, how the local government formulates a specific excess capacity exit route to implement the de-capacity task to the corresponding coal enterprises. The former issue is the research basis of the latter issue and the focus of this study.

From a methodology viewpoint, the existing research mainly uses optimization model (Wang et al., 2018b；Wang et al., 2019a), ignoring the heterogeneity of both central and local government's interests in the process of de-capacity quota allocation. In fact, the central government and local governments as the formulator and implementers of the de-capacity policy respectively, have different development goals. It is a typical bi-level optimization problem of master-slave hierarchy. Without considering the interest interaction between the central and local governments, a de-capacity quota allocation would not reflect the actual administration system in China’s coal industry. From research perspectives, the existing literature focuses primarily on the minimization of de-capacity cost and the growth rate of total factor production, and does not take into account the environmental improvement. For a long time, the unidirectional “resources - products - waste emissions” mining mode of coal leads to an ecological crisis in mine areas (Wang et al., 2019b). Under the background of ecological civilization construction, we should consider not only the economy and fairness but also the environmental improvement of the allocation scheme (Wang et al., 2019a).

Focusing on China's coal industry management system and ecological civilization construction，we constructed an allocation model of coal de-capacity quota and obtained the optimal allocation scheme in 25 coal-producing provinces[2]. This study contributes to the literature in three ways. First, considering the heterogeneity of both central and local government's interest demands, an entirely novel allocation model of coal de-capacity is constructed using bi-level multi-objective combinatorial optimization with the upper level as the central government and the lower level as the provincial government. Compared with the single-level optimal allocation scheme (SOAS) used in the previous study (Wang et al., 2019a; 2018b), this model can better reflect the complex dynamics of the game process of China's overcapacity governance system due to different in perspectives, and provides a promising decision-making tool for the Chinese governments at various levels. Second, in contrast to the existing research, which only considers minimizing de-capacity cost (Wang et al., 2018b) and improving total factor productivity (Wang et al., 2019a; Shi et al, 2019), this study is the first to incorporates environmental benefit of mining areas into the central government's de-capacity target. Third, we verified the superiority of the allocation scheme compared with the current government allocation scheme (GAS) by comparing with the current coal de-capacity task allocation plan, and the SOAS approach existing literature from four aspects: economy, efficiency, environment, and fairness. In addition, we also measured the proportion and implementation rate of the 25 coal producing provinces' de-capacity allocation under the different target preference scenarios of the central government. This will help the Chinese government to set the coal de-capacity quota allocations.

The rest of this paper is structured as follows. Section 2 reviews the literature on overcapacity and bi-level planning. Section 3 represents bi-level optimization model and data sources. Section 4 compares the results of our optimization schemes with GAS and SOAS. The conclusions and policy recommendations are given in Section 5.

## 2. Literature review

### 2.1. Measurement and causes of excess capacity

There are many measurement methods of overcapacity that originate from different theories and perspectives. Most of the existing researches use capacity utilization rate to judge the degree of overcapacity. The basic idea of this

[2] The reasons for not discussing state-owned companies are as follows: first, from the actual de-capacity situation, most state-owned companies can fulfill the de-capacity tasks allocated by the central government in advance because of the great advantages of capital, technology and mining conditions. For example, the State-owned Assets Supervision and Administration Commission of China announced that: in 2016, the state-owned companies solved a total of 34.97 million tons of coal excess capacity, with a completion rate of 109.9% ; in 2017, the central enterprises solved a total of 27.03 million tons of coal excess capacity, with a completion rate of 108.4%; second, in the administrative sequence of China, local governments and state-owned companies are at the same administrative level, and local governments do not have enough power to intervene in state-owned companies.

measure is first to estimate production output value, and then to use the ratio of actual output value and production output value to calculate the capacity utilization rate. The present methods used to measure capacity utilization are mainly the survey method (Lima and Malgarini, 2017), the peak method (Klein and Preston, 1967), the production function method (Zhang et al., 2018; Ray, 2018), and the efficiency evaluation method (Karagiannis, 2015; Arfa et al., 2017). The production function method based on economic growth theory takes into account the contribution of inputs to production capacity, and thus has strong economic significance. Using a number of economic variables, its results can obtain more information and is widely used. Therefore, the boundary production function is adopted in this study to measure the coal capacity and capacity utilization rate for each province.

Overcapacity is an economic phenomenon and scholars have studied its causes from different angles. Overcapacity, specifically cyclical overcapacity in Western countries, is mostly short-term and coincides with an economic crisis. In this regard, some scholars primarily explain the causes of overcapacity from a microscopic perspective. For example, Mathis and Koscianski (1997) discussed enterprise's behaviors using game theory and answered the question that how the decisions made by incumbents lead to overcapacity in the face of threats by potential competitors. Zhang et al. (2017) discussed the mechanism of overcapacity in China's coal industry from the perspective of government investment. Some others combine market characteristics with game theory methods, arguing that investment strategies and price strategies adopted by companies to maximize their own interests will easily lead to overcapacity (Zhao et al., 2018; Ma et al., 2019; Safarzadeh and Rasti-Barzoki, 2019). Unlike Western countries, Chinese-style overcapacity has both cyclical and non-cyclical features. In this regard, scholars focus on the causes of overcapacity around the two core points of "market failure" and "system distortion." The market failure hypothesis holds that overcapacity is primarily due to the market economy itself, that is, insufficient aggregate demand (Zhang et al., 2018), enterprise entry and exit mechanisms (Shen and Chen, 2017), micro-subject expectations (Lin et al., 2010), and other angles. The institutional distortion hypothesis argues that the imbalances in various relationships in the transitional economy are the root cause of Chinese-style overcapacity (Bao et al., 2017). The above research results provide the necessary theoretical basis and method references for this study.

## 2.2. Governance strategies for excess capacity

At present, research on managing the overcapacity of coal focus on eliminating backward production capacity and resource integration. Eliminating inefficient small businesses can both compress capacity and adjust the industry structure to achieve economies of scale in industry competition (Liu et al., 2017). To this end, the State Council of

China issued a series of documents and proposed specific tasks to eliminate backward production capacity. For example, the "*Opinions of the State Council on Reducing Overcapacity in the Coal Industry to Achieve Development by Solving the Difficulties*" issued in 2016 stipulates that "the coal mines with non-mechanized mining, those located in Shanxi, Inner Mongolia, and other four provinces and regions having capacity of less than 600,000 tons/year, those located in 11 counties such as Shandong and Jiangsu with a regional production capacity of less than 300,000 tons/year and coal mines with a capacity of less than 90,000 tons/year in other regions, will all be closed." However, in practice, due to factors such as GDP-oriented local officials' performance evaluation and employment pressure, the policy of shutting down production capacity in many regions has not been effectively implemented (Jia and Nie, 2017; Shi et al, 2018). Moreover, areas with a single economic structure often address the economic impact of small business shutdown policies by expanding the capacity of large enterprises, thus weakening the implementation of this policy (Andrews-Speed, 2005; Shi, 2013). In view of the economies of scale of large groups, enterprise resource integration and mergers and acquisitions have gradually become important in reducing capacity. However, although resource integration is conducive to controlling production capacity, mergers and acquisitions under local government administrative intervention are likely to exacerbate coal overcapacity (Zeng et al., 2016; Shi, 2013).

In summary, China has taken many measures from the aspects of economy, environment, technology, and safety to force the reform of coal supply side, and many scholars have actively explored the strategies of reducing excess capacity. However, most of these studies are based on the static perspective and focused on one single subject of the central government or the local government, which can't provide a comprehensive view of overcapacity governance. Therefore, it is important to comprehensively examine the economic, social and environmental effects of de-capacity in coal industry, and formulate a scientific overcapacity allocation scheme by multi-dimensional targets and constraints.

### 2.3. Bi-level optimization model

In view of the importance of the de-capacity allocation problem, a small number of literatures discuss the allocation method of coal de-capacity quota based on the minimization of de-capacity cost and the growth rate of total factor production (Wang et al., 2019a; Wang et al., 2018b). However, these studies ignore the heterogeneity of both central and local government's interest demands in the process of de-capacity allocation, and the improvement of the environmental benefits of mining areas brought about by de-capacity. In this paper, we fully consider the interests of the central and local governments, and use the bi-level planning method to study the problem of coal de-capacity allocation.

The bi-level optimization problem originated from a game model proposed by Strehlow and Stackelberg (1950) in the study of non-equilibrium market economy in the 1950s, to solve the problem between two decision makers. Bi-level optimization is developed from multi-objective optimization and it solves the limitation of only one decision-making body in traditional multi-objective optimization. Multi-objective optimization refers to resolve the problem of maximizing (or minimizing) multiple objective functions while satisfying a given constraint. The single-level multi-objective optimization is limited to examine the problem with multiple decision makers and their master-slave hierarchical relationship optimization. Compared to the single-level multi-objective optimization method (Wang et al., 2019a; Wang et al., 2018b), the bi-level programming is a systematic optimization model with a two-level hierarchical structure, the upper-level decision affects the lower-level target realization, while the lower-level decision affects the upper-level target realization. The upper-level problem and the lower-level problem both have their own decisions variables, constraints, and objective functions. The model can better describe the hierarchical relationship of the management department, and more fully reflect the will of the decision makers, so that the decision-making scheme can meet the requirements of decision makers at all levels, and has a wider application scenario. In the real world, the decision makers at the upper and lower levels are usually affiliated with different departments, representing different interests and having relative independence. At present, bi-level optimization has been widely used as an important optimization method and means in economic management (Quashie et al., 2018; Wang et al., 2017; Xiao et al., 2018; Whittaker et al., 2017), network planning (Londono and Lozano, 2014; He et al., 2014; Calvete et al., 2014; Baffier et al., 2018), engineering problems (Muhuri and Nath, 2019; Elsido et al., 2019), electricity pricing (Azar et al., 2018; Alves and Antunes, 2018; Savelli et al., 2018), traffic optimization (Sun et al., 2006; Jung et al., 2016; Gaspar et al., 2015) and other fields (Zeng et al., 2016; Iturriaga et al., 2017; Feijoo and Das, 2015).

Under the current management system in China, the process of allocation of coal de-capacity quotas is also a game between the central government and local governments. It is a typical bi-level optimization problem of master-slave hierarchy. The central government formulates the allocation plan based on the economic development quality and environmental quality of the coal industry, while the local government determines the execution capacity of its de-capacity quota based on its own capacity to undertake the cost of de-capacity; the game between the two directly affects the execution effect of the de-capacity quota allocation plan.

## 3. Construction of Bi-level Optimization Model

### 3.1. Problem description

In 2016, China formulated a de-capacity allocation plan, but the actual result is far from the central government's goal. For example, progress in some provinces is lagging way behind, while other provinces have reached their target capacity by reducing approved capacity on surface levels. The main reason is that the central government mainly formulates distribution plans based on the total amount of coal surplus and coal production in various provinces and regions, without considering the imbalance of economic development levels in various provinces and regions and the heterogeneity of central government and local government interests (Shi et al,, 2018). For example, de-capacity will inevitably involve laying off many people and making some fixed assets idle, resulting in personnel resettlement costs and asset losses, which will be ultimately borne by local governments. For provinces which are not highly developed, these costs will bring huge financial pressure, thus reducing their willingness to carry out de-capacity tasks. In fact, a series of changes occurred in the management system of China's coal industry since 1980. The current system can be divided into four levels: central, provincial, municipal, and county. The provincial government, as the main body of substantive policy and normative implementation, plays the most important role in the implementation of de-capacity.

In summary, since the central government and local governments act as the main decision body and executive body of industrial policies, respectively, the game between them directly affects the implementation of the de-capacity policy. From a logical relationship standpoint, the central government's goal is that the local government will remove as much excess capacity as possible, which will bring benefits that not only in improving the economic quality of the coal industry, but also in improving the environmental benefits of the mining areas which are often beyond the boundary of any individual province. The local government hopes that the central government meets its total de-capacity target which will reduce capacity, and thus lower the corresponding costs. Based on the above analysis, the interaction between the central government and the local government is a master-slave hierarchical two-level planning problem addressing the coal de-capacity quota allocation.

### 3.2. Bi-level model outline

The implementation process of central and local government capacity reduction policies can be expressed as a two-tier optimization problem, as shown in Figure 1. In this problem, the central government represents the upper level as the policy maker, while the local government represents the lower level as the implementer. The central government eliminated the excess and backward production capacity by formulating the scale of de-capacity in the coal-producing provinces in order to maximize the growth of the total factor productivity and the environmental benefits of the mining areas and pass it on to the lower-level governments. The overall goal of de-capacity in the upper layer is used as the constraint of the lower layer to determine the induced area of the underlying problem. When the lower-level local government accepts the upper-level de-capacity allocation instruction, it adjusts the execution rate[3] of its own to minimize the cost of de-capacity for themselves. The lower layer of decision information is passed back to the upper layer, and the upper layer optimizes its own target according to the lower layer decision, repeating the process until a balance point is found. At this balance point, neither of them has the motivation to change the choice. The formula of the whole bi-level optimization is described in Section 3.2.

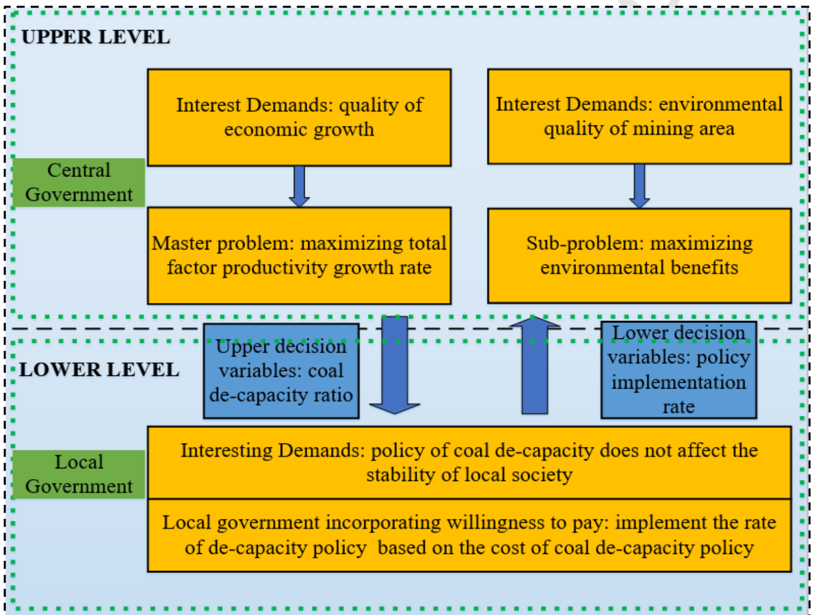


**Figure 1**. Schematic diagram of the bi-level design-operating model

### *3.2.1. Upper level model*

According to the "13th Five-Year Plan for Coal Industry Development," the three major problems faced by the coal industry are: overcapacity, prominent industrial structure contradictions and serious damage to the ecological environment of the mining area. To solve these problems, the central government not only needs to reduce coal

[3] The policy implementation rate refers to the degree to which the local government is willing to implement the de-capacity tasks allocated by the central government in consideration of coal de-capacity costs. The central government mainly sets the plan for the allocation of capacity quotas based on the development of the industrial economy and the improvement of environmental quality. The local government, as the specific executor of the task of de-capacity, pays more attention to the cost of de-capacity. If the cost of de-capacity exceeds the capacity of local governments, under the condition of information asymmetry, local governments will not fully implement the task of de-capacity; on the contrary, local governments will actively implement the goal of de-capacity.

surplus and backward production capacity, but more importantly, optimize the coal industrial structure and improve the ecological environment of the mining area. Total factor productivity ( $T\dot{F}P$ )[4], as an important indicator to measure the quality of economic growth, can reflect the efficiency of the overall economic condition, turning inputs into output. In addition, China's resource constraints are tightening due to serious environmental pollution issues, and the ecological environment constraints of coal development are also strengthened. If the province does not implement the coal de-capacity policy, surplus and backward production capacity will bring huge ecological damage to the mining area. Therefore, we will implement the growth rate of total factor productivity after de-capacity and the environmental benefits of the mining area, as the development goals of the central government.

On the one hand, the "*13th Five-Year Plan for China's Coal and Coal Industry Development*" jointly issued by the National Development and Reform Commission and the National Energy Administration in December 2016, puts forward the overall goal of national coal de-capacity to resolve the excess capacity of coal by 2020. On the other hand, the minimum coal production in the Northeast, Eastern, Central and Western regions was determined in order to ensure the regional coal market demand and optimize the coal development layout. Therefore, we will take 2020's national coal de-capacity of 800 million tons and the regional minimum coal production as the upper constraints. Based on the above analysis, we build the upper model as shown in formula (1):

$$\max T\dot{F}P = \sum_{i=1}^{25}\left\{ Y_e - Y_{oi} - \alpha_i Y_{oi}\left\{ \left[ Y_{si}^*\left(1-R_iK_i\right)e^{-\hat{\lambda}_i}\left(\frac{\hat{\alpha}_i w_i}{\hat{\beta}_i r_i}\right)^{\beta_i}\right]^{\frac{1}{\alpha_i+\beta_i}} - K_{oi}\right\} \Big/ K_{oi} - \beta_i Y_{oi}\left\{ \left[ Y_{si}^*\left(1-R_iK_i\right)e^{-\hat{\lambda}_i}\left(\frac{\hat{\alpha}_i w_i}{\hat{\beta}_i r_i}\right)^{-\alpha_i}\right]^{\frac{1}{\alpha_i+\beta_i}} - L_{oi}\right\} \Big/ L_{oi}\right\} \Big/ \sum_{i=1}^{25} Y_{oi}$$

$$\max C_e = \sum_{i=1}^{25}\sum_{j=1}^{3} Y_{si}^* R_i K_i \frac{CU_{\max}+CU_{\min}}{2}\mu_j \varphi_{ij}$$

$$s.t.\begin{cases} \sum_{i=1}^{25} Y_{si}^* R_i K_i = \Delta Y_T^*,\ 0 \le R_i K_i \le 1, 0 \le R_i \le 1, 0 \le K_i \le 2, i = 1,2,\ldots,25 \\ CO_1/CU_{\max} \le \sum_{i=1}^{3} Y_{si}^*(1-R_iK_i) \le CO_1/CU_{\min} \\ CO_2/CU_{\max} \le \sum_{i=4}^{8} Y_{si}^*(1-R_iK_i) \le CO_2/CU_{\min} \\ CO_3/CU_{\max} \le \sum_{i=9}^{14} Y_{si}^*(1-R_iK_i) \le CO_3/CU_{\min} \\ CO_4/CU_{\max} \le \sum_{i=15}^{25} Y_{si}^*(1-R_iK_i) \le CO_4/CU_{\min} \end{cases} \quad (1)$$

[4] Xi Jinping's report at the 19th National Congress of the Communist Party of China pointed out that improving total factor productivity is the source of power for high-quality development. It is of great significance for China's decision to build a well-off society and start a new journey of building a socialist modern country. The total factor productivity is essentially a resource allocation efficiency. The resource reconfiguration caused by industrial structure optimization, enterprises competition and innovation competition can improve the total factor productivity.

Among them, $T\dot{F}P$ is the growth rate of total factor productivity[5]; $Y_e$ is the coal production in 2020 under the condition of completing the de-capacity target; $Y_{oi}$ is the actual coal production of the province $i$ in 2015; $Y_{si}^*$ is the capacity output of the province $i$ without implementing the de-capacity task in 2020; $K_{oi}$ is the actual capital investment of the coal industry in the province $i$ in 2015; $L_{oi}$ is the actual labor input of the coal industry in the province $i$ in 2015; $R_i$ is the decision-making variable of the upper central government, indicating the proportion of province $i$ capacity withdrawal scale to the province's coal production capacity. $K_i$ is the decision-making variable of the lower local government, indicating the execution rate of the province $i$ de-capacity task; $C_e$ is the environmental benefit of mining area, and we will estimate the emission reduction of three wastes (exhaust gas, waste water and waste residue) in the mining area of each province after removing the capacity of coal, so that the emission reduction of these three wastes in each province can be converted into the cost of controlling the environment of the mining area accordingly; $\mu_j$ represents the $j$ pollutant emission coefficient; $\varphi_{ij}$ represents the environment of the $j$ pollutant in the province $i$ Value (i.e., the cost of controlling the pollutant); $CO_1$, $CO_2$, $CO_3$ and $CO_4$ represent the coal production requirements in 2020 for the Northeast, East, Central and Western regions, respectively. $CU_{\min}$ and $CU_{\max}$ represent the lower and upper limits of reasonable productivity utilization ratio, respectively, and $\Delta Y_T^*$ represents the total volume of capacity reduction in the coal industry.

### *3.2.2. Lower level model*

Since China's coal industry is still labor-intensive and requires a large number of equipment, the implementation of the de-capacity policy will inevitably lead to laying off a large number of people and having many idle fixed assets. According to the theory of production factors, we divide the total cost of coal de-capacity into two parts: labor placement costs and fixed asset disposal costs[6]. Most of these costs need to be borne by local governments. Therefore, the interests of local governments are the minimum cost of implementing coal de-capacity policies. Similarly, local governments also need to meet the constraints of the coal production capacity of 800 million tons and the minimum production of regional coal as stipulated in the “13th Five-Year Plan for China's Coal and Coal Industry Development” jointly issued by the National Development and Reform Commission and the National Energy Administration in December 2016.

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5 In this paper, we use Solow Remainder Method to measure the growth of total factor production. The specific method is shown in Appendix C.

6 For the specific estimation method of labor resettlement cost and fixed asset disposal cost, see Appendix B.

Based on the above analysis, the lower model is constructed as shown in formula (2):

$$\min TC_i(R_i,K_i) = r_i\left\{K_{si}-\left[Y_{si}^*\left(1-R_iK_i\right)e^{-\hat{\lambda}_i}\left(\frac{\hat{\alpha}_i w_i}{\hat{\beta}_i r_i}\right)^{\hat{\beta}_i}\right]^{\frac{1}{\hat{\alpha}_i+\hat{\beta}_i}}\right\}+w_i\left\{L_{si}-\left[Y_{si}^*\left(1-R_iK_i\right)e^{-\hat{\lambda}_i}\left(\frac{\hat{\alpha}_i w_i}{\hat{\beta}_i r_i}\right)^{-\hat{\alpha}_i}\right]^{\frac{1}{\hat{\alpha}_i+\hat{\beta}_i}}\right\}$$

$$s.t.\begin{cases}\sum_{i=1}^{25}Y_{si}^*R_i \ge \Delta Y_T^*,\ 0\le R_iK_i\le 1, 0\le R_i\le 1, 0\le K_i\le 2, i=1,2,\ldots,25\\ CO_1/CU_{\max}\le\sum_{i=1}^{3}Y_{si}^*(1-R_i)\le CO_1/CU_{\min}\\ CO_2/CU_{\max}\le\sum_{i=4}^{8}Y_{si}^*(1-R_i)\le CO_2/CU_{\min}\\ CO_3/CU_{\max}\le\sum_{i=9}^{14}Y_{si}^*(1-R_i)\le CO_3/CU_{\min}\\ CO_4/CU_{\max}\le\sum_{i=15}^{25}Y_{si}^*(1-R_i)\le CO_4/CU_{\min}\end{cases} \quad (2)$$

Among them, $TC_i\left(R_i,K_i\right)$ is the coal de-capacity cost of the province $i$, $r_i$ is the de-capacity asset loss rate of the province $i$ coal industry; $K_{si}$ is the capital investment of the coal industry in 2020 when province $i$ does not implement the de-capacity task; $w_i$ is the per capita social cost of eliminating capacity of province $i$; $L_{si}$ is the labor input of the coal industry in the 2020 province when province $i$ does not implement the de-capacity task.

### 3.3. Model solution

The bi-level optimization problem is a typical NP-hard problem with no polynomial solving algorithm (Ben Ayed et al., 1988). An important reason for the extremely complex two-layer optimization problem is its non-convexity. Even if you can find the solution to the two-layer problem, it will possibly be a local rather than a global optimal solution. Therefore, in this paper, we will use Particle Swarm Optimization (PSO)to solve the complexity of the model and the non-convexity of the lower layer.

First, because of the cost function of the 25 provinces in the underlying problem, and the dimensions are the same, we combine the 25 cost functions into a single objective function by linear weighting. The formula for the underlying problem can be converted as follows:

$$\min TC(R_i,K_i)=\frac{1}{25}\sum_{i=1}^{25}\left\{r_i\left\{K_{si}-\left[Y_{si}^*\left(1-R_iK_i\right)e^{-\hat{\lambda}_i}\left(\frac{\hat{\alpha}_i w_i}{\hat{\beta}_i r_i}\right)^{\hat{\beta}_i}\right]^{\frac{1}{\hat{\alpha}_i+\hat{\beta}_i}}\right\}+w_i\left\{L_{si}-\left[Y_{si}^*\left(1-R_iK_i\right)e^{-\hat{\lambda}_i}\left(\frac{\hat{\alpha}_i w_i}{\hat{\beta}_i r_i}\right)^{-\hat{\alpha}_i}\right]^{\frac{1}{\hat{\alpha}_i+\hat{\beta}_i}}\right\}\right\} \quad (3)$$

Then a membership function is established for each target of the upper layer, that is, the membership degree of the total factor productivity growth rate and the environmental benefit cost function. They are as follows：

$$Z_1 = \begin{cases} 1, & T\dot{F}P \geq T\dot{F}P_{\max} \\ \dfrac{T\dot{F}P - T\dot{F}P_{\min}}{T\dot{F}P_{\max} - T\dot{F}P_{\min}}, & T\dot{F}P_{\min} \leq T\dot{F}P \leq T\dot{F}P_{\max} \\ 0, & T\dot{F}P \leq T\dot{F}P_{\min} \end{cases} \tag{4}$$

$$Z_2 = \begin{cases} 1, & C_e \geq C_{e\max} \\ \dfrac{C_e - C_{e\min}}{C_{e\max} - C_{e\min}}, & C_{e\min} \leq C_e \leq C_{e\max} \\ 0, & C_e \leq C_{e\min} \end{cases} \tag{5}$$

$TFP_{\min}$ and $TFP_{\max}$ represent the possible minimum and maximum growth rates of total factor productivity respectively while $C_{e\min}$ and $C_{e\max}$ represent the possible minimum and maximum environmental benefits of mining areas respectively.

Then, the above membership functions (4) and (5) are transformed into single objective functions by using linear weighting method.

$$\max\ Z = \lambda_1 Z_1 + \lambda_2 Z_2 \tag{6}$$

Among them, $\lambda_1$ and $\lambda_2$ are calculated weights.

According to the cost function and constraints in the lower model, the solution of the optimization problem of linearly weighted single objective cost function is obtained and the minimum value $TC_{\min}$ and the maximum value $TC_{\max}$ of the de-capacity costs are obtained. Similarly, by finding the solution of the single objective optimization problem of total factor productivity growth rate, the minimum value $TFP_{\min}$ and the maximum value $TFP_{\max}$ of the total factor productivity growth rate and the minimum value $C_{e\min}$ and maximum value $C_{e\max}$ of the environmental benefit of the mining area are obtained.

Finally, according to formulas (4) and (5), the membership degree of the total factor productivity growth rate and the environmental benefit of the mining area are measured, respectively, the weighted total membership degree is obtained according to formula (6), and the double-layer multi-objective conversion is performed. It is a two-level plan with a single target in both upper and lower layers. It is then solved by PSO algorithm. The steps of the PSO algorithm are as follows:

Step 1: Generating an initial solution R0 of the upper decision variable R according to the constraint condition of the upper layer planning problem and initialize fbest = INF;

Step 2: Set k=1, given the number of iterations M;

Step 3: Substituting R0 into the lower layer of the second-level plan, using the particle swarm optimization algorithm to solve the lower layer problem to obtain the optimal solution K0;

Step 4: Returning the obtained K0 value to the upper layer and use the particle swarm optimization algorithm to solve the upper layer problem to obtain the optimal solution R0 and the corresponding optimal value f;

Step 5: If f<fbest, then update fbest = f, Rbest = R, Kbest = K0, otherwise go to step 6;

Step 6: If the end condition is satisfied (the error is good enough or the maximum number of iterations is reached), let R0 = Rbest, k=k+1, then go to step 3;

Step 7: Output the optimal value of R, K Rbest, Kbest;

### 3.4. Data Sources

China's resources are mainly distributed in 25 provinces and autonomous regions (hereafter provinces). The locations and coal outputs of the 25 provinces in 2018 are shown in Figure 2 and the measurement methods of related parameters and data sources are shown in Table 1.

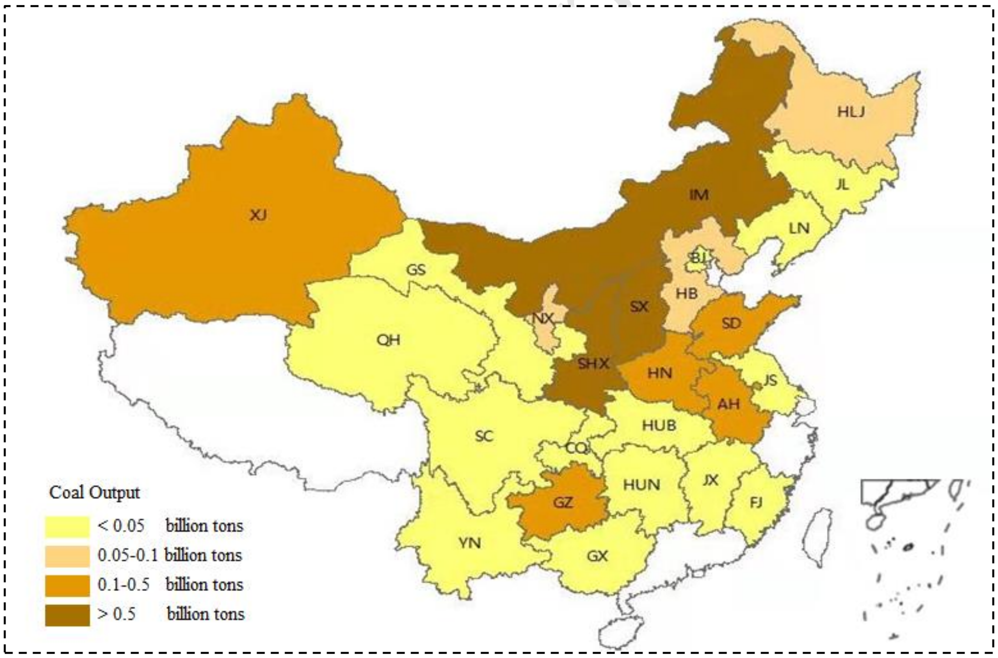


**Figure 2.** Location and coal output in 2017 of the 25 coal-producing provinces in China[7]

[7] In the map, LN represents Liaoning, JL represents Jilin, HLJ represents Heilongjiang, they are all in northeast China; Similarly, BJ, HB, JS, FJ and SD represent Beijing, Hebei, Jiangsu, Fujian and Shandong respectively, they are all in eastern China ; SX, AH, JX, HN, HUB, HUN represent Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan respectively, they are all in central China; IM, GX, CQ, SC, GZ, YN, SX, GS, QH, NX and XJ represent Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang respectively, they are all in western China.

**Table 1** Measurement methods of related parameters and data sources

| Symbol | Symbol definition | Measurement method | Data sources |
|---|---|---|---|
| $Y_e$ | Complete coal production in 2020 under the condition of de-capacity | Guided by *the Thirteenth Five-Year Development Plan for the Coal Industry*, which reads: "China's coal output will be controlled within 39 billion tons by 2020," we let $Y_e$ = 390,000 (unit: 10,000 tons) | *The Thirteenth Five-Year Development Plan for the Coal Industry (2016)* |
| $Y_{si}^*$ | The capacity of the i-th province does not implement the task of de-capacity in 2020 (unit: 10,000 tons) | Provincial boundary production function | Appendix A |
| $Y_{oi}$ | Production capacity of the coal industry in the i-th province in 2015 (unit: 10,000 tons) | Measured by raw coal output of coal industry in provinces in 2015 (unit: 10,000 tons) | *Statistical Yearbooks by Provinces (2016)* |
| $K_{oi}$ | Capital investment in coal industry in the i-th province in 2015 | Measured by balance of fixed assets of coal industry in provinces in 2015 (unit: 100 million yuan, in constant 1990 prices) | *China Industrial Economics Statistical Yearbook (2016)* |
| $L_{oi}$ | Labor input of coal industry in the i-th province in 2015 | Measured by average number of employees in the coal industry in provinces in 2015 (unit: 10,000 people) | *China Price Statistics Yearbook 2016* |
| $K_{si}$ | The i province does not implement the task of de-capacity and coal industry capital investment in 2020 | Provincial boundary production function | Appendix A |
| $L_{si}$ | The i province does not implement the task of de-capacity and the labor input of the coal industry in 2020 | Provincial boundary production function | Appendix A |
| $\mu_j$ | Item j pollutant emission coefficient (exhaust gas, waste water, waste residue) | $\mu_1$ =3.3tons, $\mu_2$ =4cubic meter, $\mu_3$ =0.2tons | |
| $\varphi_{ij}$ | Environmental value of the jth pollutant in the i province (governance cost) | the proportion of investment in pollution control of three wastes in the coal industry of each province accounted for the amount of disposal of three wastes | *China Environmental Statistics Yearbook 2016* |
| $w_i$ | The per capita social cost of coal de-capacity in the i-th province | Measured by daily living costs, social insurance costs, employment costs, and education costs in provinces | Appendix C |
| $r_i$ | The loss rate of de-capacity assets in the coal industry in the i-th province | Measured by the recoverable amount of fixed assets of coal mines with net residual value | Appendix C |
| $\Delta Y_T^*$ | Total de-capacity coal production | Following the *Thirteenth Five-Year Development Plan for the Coal Industry*, which reads "withdraw 800 million tons of coal capacity by 2020," we let $\Delta Y_T^*$ =80,000 (unit: 10,000 tons) | |
| $CO_1$ | Coal production requirements in Northeast China by 2020 | The coal output requirements of Northeastern China in 2020, $CO_1$ = 12,000 (unit: 10,000 tons) | *The Thirteenth Five-Year Development Plan for the Coal Industry (2016)* |
| $CO_2$ | Coal production requirements in the eastern region in 2020 | The coal output requirements of Eastern China in 2020, $CO_2$ = 17,000 (unit: 10,000 tons) | |
| $CO_3$ | Central coal production requirements in 2020 | The coal output requirements of Central China in 2020, $CO_3$ = 130,000 (unit: 10,000 tons) | |
| $CO_4$ | Coal production requirements in the western region in 2020 | The coal output requirements of Western China in 2020, $CO_4$ = 231,000(unit:10,000tons) | |
| $CU_{\min}$ | Lower limit of reasonable capacity utilization interval | The lower limit of the reasonable capacity utilization rate interval; we set $CU_{\min}$ = 0.79 | Kou et al., 2017 |
| $CU_{\max}$ | The upper limit of the reasonable capacity utilization interval | The upper limit of the reasonable capacity utilization rate interval; we set $CU_{\max}$ = 0.83 | Kou et al., 2017 |
| $\hat{\lambda}_i$ | Production efficiency coefficient of the i-th province | Provincial boundary production function | Appendix A |
| $\hat{\alpha}_i$ | Output elasticity coefficient of capital input factors in the i-th province | Provincial boundary production function | Appendix A |
| $\hat{\beta}_i$ | Output elasticity coefficient of labor input factors in the i-th province | Provincial boundary production function | Appendix A |

# 4. Results

## 4.1. Optimal scheme for coal de-capacity allocation

According to the "*Opinions on Eliminating Excess Production Capacity and Realizing Overcoming Difficulties in the Iron and Steel and Coal Industry in 2017*" released by the State Council of China, the central government needs to improve the economic development quality of the coal industry and the ecological environment of the mining area but it pays more attention to the economic status of the coal industry due to its substantial losses and low profitability. Therefore, we surmise that the central government has a greater preference for the growth rate than the ecological benefits of the mining area and the value of preference is calculated as follows: $[\lambda_1, \lambda_2] = [0.7, 0.3]$. Using the compiled algorithm of MATLAB 2015 and setting the number of particles N to 40, the learning factor c1 to 1.5, the training factor c2 to 1.5, the inertia weight w to 0.6, the maximum number of iterations to 2000, and the penalty coefficient s to 1000000, we solve the above two-layer optimization model and obtain the optimal allocation scheme of coal overcapacity reduction, which is the allocation ratio of the upper central government and the policy implementation rate and the cost of overcapacity reduction of each province and region.

As shown in Table 2, the six provinces with the largest scale of overcapacity reduction are IM, SX, SHX, GZ, SD, and HN, they account for 60.33% of the total overcapacity reduction target. The six provinces with the least capacity to decommission are GX, FJ, BJ, QH, HUB, and NX, they account for 4.95% of the total overcapacity reduction target. It can be seen that a few provinces have undertaken the main task of coal overcapacity reduction. Moreover, these provinces that have more capacity reduction tasks have more abundant coal resource. For example, IM, SX, SHX, and SD are China's major coal-producing provinces (see Figure 2). These enlightening findings are that provinces with abundant coal reserves and large output are often also the hardest hit areas with excess capacity. Therefore, the key to the successful implementation of China's coal capacity reduction task is to first solve the problem of overcapacity in major coal-producing provinces such as IM, Shanxi, and Shaanxi.

In addition, as shown in Table 2, the provinces with implementation rates exceeding 100% are LN, JS, FJ, IM, GX, GZ, SHX, GS, and QH, which demonstrates that these provinces and regions have exceeded the overcapacity reduction tasks allocated by the upper central government and have a higher preference for overcapacity reduction. The provinces with implementation rates below 80% are HLJ, AH, HUN, SC, and NX, indicating that these provinces have not fully implemented overcapacity reduction tasks assigned by the upper central government and the degree of willingness to reduce overcapacity was low.

To analyze the relationships between the policy implementation rate the cost of unit de-capacity and the GDP growth rate of the 25 provinces, we constructed a relationship map, as shown in Figure 3. Among the 15 provinces where the capacity reduction execution rate is less than 100%, some have higher cost of capacity reduction, such as SX, SD, AH, whose unit cost are 0.507,0.592,0.526 (unit: 100 million yuan/10,000 ton) respectively. The coal industry in these provinces plays an important role in the regional industrial structure. Moreover, their coal industry is heavily labor intensive, the labor placement costs are relatively high; others have relatively low GDP growth rate, such as JL, HB, and HLJ, which are 5.3%, 6.7%, and 6.4%, respectively. These provinces have developed heavy industries and have high dependence on coal resources for economic development. In a word, due to difference in geographical location, resource endowment, industrial structure, labor l and other conditions, there are differences in de-capacity costs and economic development levels in each province. Local governments, according to their own affordable de-capacity cost and level of economic development, implement the de-capacity tasks formulated by the central government with different degrees, reflecting different levels of willingness to reduce overcapacity. The execution rate of the overcapacity reduction policy is lower in the provinces with higher costs of unit withdrawal capacity and lower level of economic development.

Since there are differences in the willingness of the 25 coal-producing provinces to reduce overcapacity, we try to group them according to allocation ratio and implementation rate to explore the reasons. The results are shown as in Figure 4. In Group Ⅰ, there are three provinces, i.e. GZ, SHX and IM. These provinces are all coal resource-based provinces with rich coal resources. As the main provinces for capacity reduction, they bear more de-capacity quotas than others and are highly motivated to execute the given task. The provinces distributed in Group II are SX, SD and HN, which undertake a high proportion of capacity reduction. However, as the coal industry occupies a more important role in these provinces, capacity reduction may affect the local economic development. They generally hold a negative attitude towards capacity reduction. 13 provinces are densely distributed in Group III. Although these provinces undertake a small amount of capacity reduction, they can’t fully implement the de-capacity tasks, and have a lower willingness to execute the given quotas. Therefore, when the central government monitors the effect of overcapacity reduction, these provinces should be the focus of attention. There are 7 provinces in Group IV, such as LN, GS, QH and so on. They are active in capacity reduction and even over-fulfill the task. This may be related to their low capacity reduction costs and slight pressure on de-capacity. For example, QH's de-capacity cost is only 0.214 (unit: 100 million yuan/10,000 ton).

**Table 2** Bi-level optimized allocation scheme of coal de-capacity

| Province | $\dot{TFP}$ =7.92%, $C_e$ =12440, $TC$ =3126.201 | | | |
|---|---|---|---|---|
| | Reduction scale | Allocation ratio | Policy implementation rate | Reduction proportion |
| LN | 2210.783 | 2.763% | 102.920% | 27.460% |
| JL | 2493.749 | 3.117% | 83.060% | 45.560% |
| HLJ | 2365.098 | 2.956% | 76.150% | 29.430% |
| BJ | 520.000 | 0.650% | 100.000% | 100.000% |
| HB | 2998.955 | 3.749% | 82.750% | 29.410% |
| JS | 1212.805 | 1.516% | 107.610% | 45.630% |
| FJ | 502.345 | 0.628% | 122.820% | 19.040% |
| SD | 5832.610 | 7.291% | 88.490% | 38.580% |
| SX | 9893.000 | 12.366% | 84.250% | 8.170% |
| AH | 2553.278 | 3.192% | 78.250% | 17.740% |
| JX | 1526.645 | 1.908% | 83.500% | 49.550% |
| HN | 5149.949 | 6.437% | 81.320% | 34.090% |
| HUB | 952.159 | 1.190% | 95.450% | 44.530% |
| HUN | 1349.013 | 1.686% | 77.710% | 33.010% |
| IM | 12713.470 | 15.892% | 182.200% | 5.250% |
| GX | 440.485 | 0.551% | 114.970% | 37.650% |
| CQ | 1802.513 | 2.253% | 87.850% | 39.960% |
| SC | 2684.263 | 3.355% | 75.980% | 26.960% |
| GZ | 7208.803 | 9.011% | 142.990% | 15.920% |
| YN | 2592.380 | 3.240% | 95.640% | 25.910% |
| SHX | 7473.435 | 9.342% | 109.520% | 10.320% |
| GS | 1924.817 | 2.406% | 128.520% | 13.610% |
| QH | 576.256 | 0.720% | 165.400% | 9.650% |
| NX | 964.023 | 1.205% | 73.760% | 9.050% |
| XJ | 2059.834 | 2.575% | 83.300% | 7.540% |
| Country | 80000.670 | 100.000% | | 13.945% |

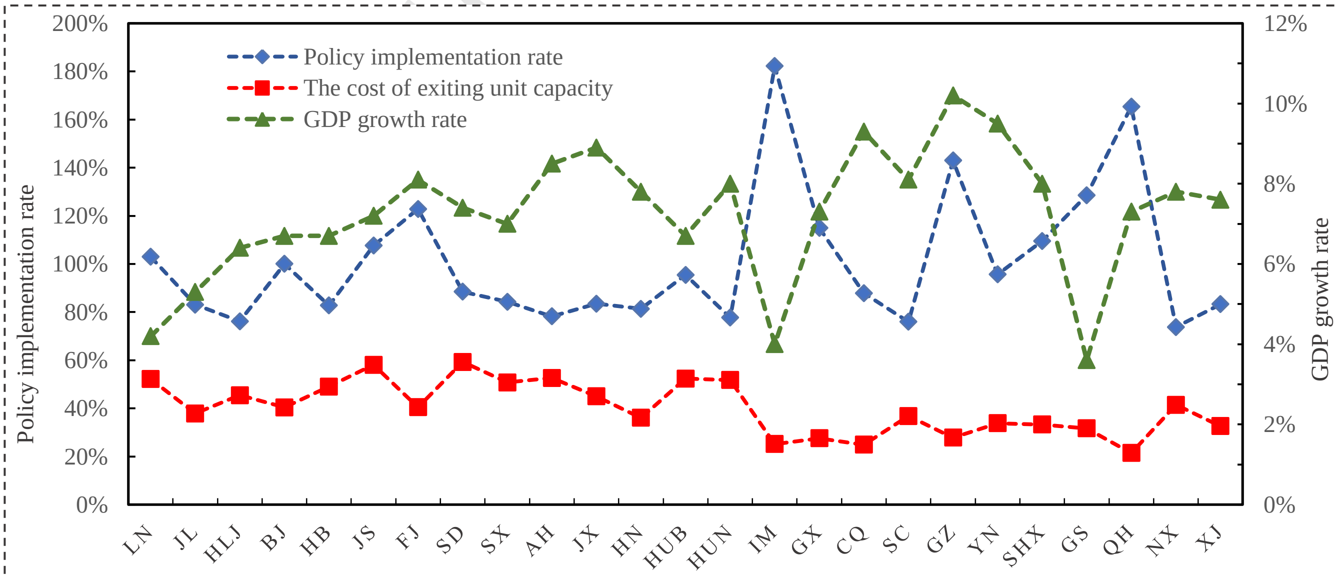


**Figure 3.** Implementation rate, the cost of exiting unit capacity and GDP growth rate of 25 provinces

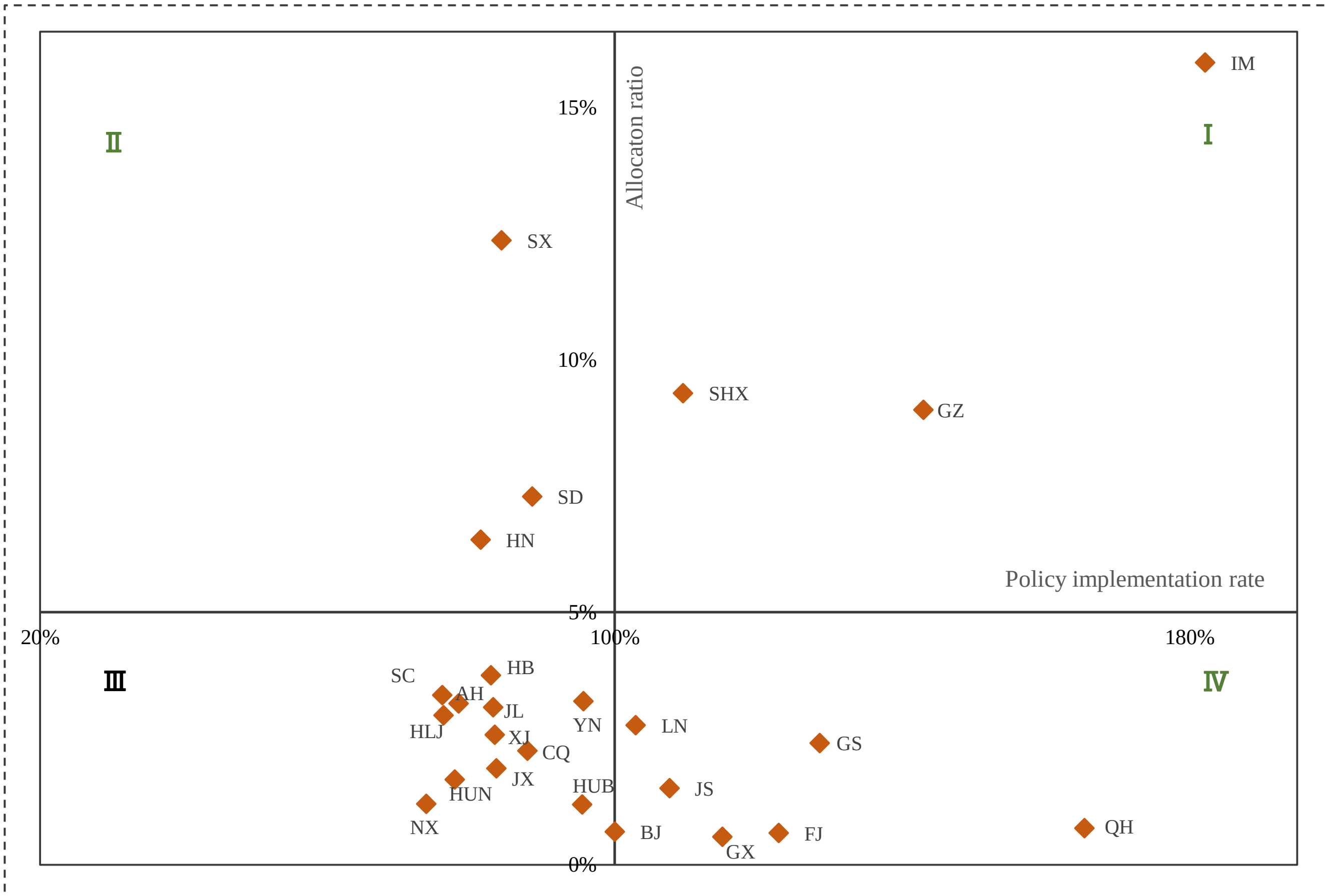


**Figure 4.** Grouping of 25 provinces by allocation ratio and policy implementation rate

## 4.2. Comparative analysis of BOAS, GAS and SOAS

In order to investigate the effectiveness and rationality of the allocation scheme of the above optimization model, this paper considers GAS proposed in 2016 by the National Development and Reform Commission and SOAS proposed by Wang et al. (2019), and makes comparative analysis from four aspects of economy, efficiency, environmental protection and distribution fairness[8]. The results are shown in Table 3.

### *4.2.1. Comparative analysis of de-capacity cost*

According to the GAS, the provinces and regions with the largest amount of overcapacity reduction are SX, GZ, SD, HN and IM account for 14.250%, 9.268%, 8.075%, 7.893% and 7.679%, respectively. The five provinces

[8] In order to enhance the rigor and integrity of this study, we also compared the BOAS with GAS, SOAS and the optimal allocation scheme (OAS) proposed by Wang et al. (2018b) from four aspects of economy, efficiency, environmental protection and distribution fairness. The comparison results show that the advantage ranking of four schemes is BOAS、GAS、SOAS and OAS. It should be noted that although the latter two schemes are both calculated by the single-level multi-objective optimization model, the difference is that the OAS only considers the target of cost minimization in modeling, ignoring the constraints of economic and production benefits in the process of de-capacity. As a result, the SOAS is better and more realistic than the OAS. Therefore, we only report the comprehensive analysis results of BOAS, GAS and SOAS here to avoid confusion and increase the readability.

account for 47.164% of the country's total amount of overcapacity reduction, which is not far from the corresponding proportion of the BOAS (50.997%). According to the SOAS, the provinces and regions with the largest amount of overcapacity reduction are SX, HN, SD, SHX, SC and AH, accounting for 12.37%, 9.74%, 9.31%, 7.79%, 5.81% and 5.21%, respectively. The six provinces account for 50.23% of the country's total amount of overcapacity reduction, which is higher than the BOAS (41.983%). Compared with the BOAS, the six provinces and regions with the largest overcapacity reduction task based on the SOAS are under greater overcapacity reduction pressure.

**Table 3** Optimized and policy schemes of coal de-capacity

| Province | BOAS | | | | | GAS | | | | | SOAS | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\dot{TFP}$ =7.92% | | | | | $\dot{TFP}$ =5.78% | | | | | $\dot{TFP}$ =7.32% | | | | |
| | Reduction scale | Environmental benefits | Total cost | Disposal cost of fixed assets | Labor resettlement cost | Reduction scale | Environmental benefits | Total cost | Disposal cost of fixed assets | Labor resettlement cost | Reduction scale | Environmental benefits | Total cost | Disposal cost of fixed assets | Labor resettlement cost |
| LN | 2210.783 | 340.000 | 115.345 | 68.583 | 46.762 | 3040.000 | 470.000 | 171.342 | 102.734 | 68.608 | 2087.000 | 320.000 | 108.876 | 64.717 | 44.160 |
| JL | 2493.749 | 390.000 | 94.528 | 42.910 | 51.618 | 2733.000 | 420.000 | 108.260 | 49.710 | 58.550 | 3616.000 | 550.000 | 137.013 | 62.158 | 74.855 |
| HLJ | 2365.098 | 370.000 | 107.469 | 71.645 | 35.824 | 2567.000 | 400.000 | 133.974 | 89.951 | 44.023 | 4079.000 | 630.000 | 185.316 | 123.482 | 61.835 |
| BJ | 520.000 | 80.000 | 20.989 | 5.070 | 15.919 | 520.000 | 80.000 | 20.989 | 5.109 | 15.880 | 520.000 | 80.000 | 20.989 | 5.109 | 15.880 |
| HB | 2998.955 | 470.000 | 147.026 | 68.835 | 78.191 | 5103.000 | 630.000 | 299.667 | 141.886 | 157.781 | 3369.000 | 530.000 | 165.105 | 77.246 | 87.860 |
| JS | 1212.805 | 190.000 | 70.447 | 43.444 | 27.003 | 1182.000 | 140.000 | 73.749 | 45.841 | 27.908 | 1362.000 | 200.000 | 79.112 | 48.773 | 30.339 |
| FJ | 502.345 | 80.000 | 20.323 | 6.561 | 13.762 | 600.000 | 90.000 | 35.053 | 11.484 | 23.569 | 333.000 | 50.000 | 16.105 | 5.192 | 10.912 |
| SD | 5832.610 | 910.000 | 345.774 | 234.367 | 111.407 | 6460.000 | 1090.000 | 419.923 | 286.537 | 133.386 | 7448.000 | 1160.000 | 441.465 | 299.136 | 142.329 |
| SX | 9893.000 | 1530.000 | 502.021 | 343.467 | 158.554 | 11400.000 | 1810.000 | 677.955 | 466.993 | 210.962 | 9893.000 | 1530.000 | 502.313 | 343.485 | 158.828 |
| AH | 2553.278 | 400.000 | 134.395 | 85.746 | 48.649 | 3258.000 | 480.000 | 202.917 | 130.484 | 72.432 | 4170.000 | 650.000 | 219.534 | 139.971 | 79.563 |
| JX | 1526.645 | 240.000 | 68.666 | 35.703 | 32.963 | 1868.000 | 270.000 | 92.121 | 48.387 | 43.734 | 2191.000 | 340.000 | 98.466 | 51.165 | 47.300 |
| HN | 5149.949 | 800.000 | 185.638 | 111.410 | 74.228 | 6314.000 | 940.000 | 290.609 | 176.020 | 114.590 | 7790.000 | 1160.000 | 280.728 | 168.260 | 112.468 |
| HUB | 952.159 | 150.000 | 49.847 | 25.457 | 24.390 | 800.000 | 100.000 | 49.397 | 25.497 | 23.900 | 1045.000 | 130.000 | 54.731 | 27.926 | 26.806 |
| HUN | 1349.013 | 210.000 | 69.843 | 28.606 | 41.237 | 1500.000 | 230.000 | 87.512 | 36.306 | 51.206 | 2234.000 | 340.000 | 115.645 | 47.313 | 68.331 |
| IM | 12713.470 | 1970.000 | 320.258 | 246.935 | 73.323 | 6143.000 | 910.000 | 179.323 | 138.942 | 40.381 | 3830.000 | 560.000 | 96.479 | 74.364 | 22.114 |
| GX | 440.485 | 70.000 | 12.158 | 4.417 | 7.741 | 473.000 | 70.000 | 14.264 | 5.251 | 9.013 | 334.000 | 50.000 | 9.191 | 3.337 | 5.854 |
| CQ | 1802.513 | 280.000 | 44.943 | 21.369 | 23.574 | 2300.000 | 300.000 | 65.625 | 31.554 | 34.071 | 2337.000 | 300.000 | 58.232 | 27.666 | 30.566 |
| SC | 2684.263 | 420.000 | 98.862 | 35.638 | 63.224 | 3303.000 | 490.000 | 100.232 | 36.633 | 63.599 | 4651.000 | 690.000 | 124.477 | 44.823 | 79.654 |
| GZ | 7208.803 | 1120.000 | 200.404 | 103.356 | 97.048 | 7414.000 | 1130.000 | 254.351 | 132.506 | 121.844 | 3526.000 | 540.000 | 110.236 | 56.827 | 53.409 |
| YN | 2592.380 | 400.000 | 87.763 | 55.422 | 32.341 | 2178.000 | 280.000 | 80.596 | 51.287 | 29.309 | 2835.000 | 360.000 | 95.965 | 60.580 | 35.385 |
| SHX | 7473.435 | 1160.000 | 248.853 | 179.629 | 69.224 | 4706.000 | 570.000 | 185.528 | 134.729 | 50.799 | 6231.000 | 750.000 | 207.451 | 149.666 | 57.785 |
| GS | 1924.817 | 300.000 | 61.032 | 34.307 | 26.725 | 1000.000 | 120.000 | 36.372 | 20.637 | 15.735 | 1166.000 | 140.000 | 36.940 | 20.751 | 16.189 |
| QH | 576.256 | 90.000 | 12.368 | 6.997 | 5.371 | 276.000 | 30.000 | 10.285 | 5.873 | 4.412 | 211.000 | 20.000 | 6.717 | 3.797 | 2.920 |
| NX | 964.023 | 150.000 | 39.969 | 19.781 | 20.188 | 1119.000 | 160.000 | 39.125 | 19.571 | 19.554 | 1772.000 | 250.000 | 55.117 | 27.260 | 27.857 |
| XJ | 2059.834 | 320.000 | 67.280 | 49.600 | 17.680 | 3743.000 | 500.000 | 139.336 | 103.292 | 36.044 | 2970.000 | 400.000 | 96.967 | 71.461 | 25.505 |
| Total | 80000.670 | 12440.000 | 3126.201 | 1929.253 | 1196.948 | 80000.000 | 11710.000 | 3768.505 | 2297.214 | 1471.290 | 80000.000 | 11730.000 | 3323.170 | 2004.465 | 1318.704 |

The comparison between the BOAS and the GAS shows that the BOAS effectively reduces the total cost of overcapacity reduction. As shown in Table 3, the total cost of the BOAS is reduced by 64 billion yuan compared with the GAS, which is reduced by 17.04%. Among them, the loss of assets decreased by 37 billion yuan, and the cost of labor resettlement decreased by 27 billion yuan. This is because, compared with the GAS, the provinces and regions with increasing the amount of overcapacity reduction under the BOAS are mainly IM, SHX, GS, YN, DH and other provinces. Most of these provinces and regions are in the economically underdeveloped western regions, where the wage level is relatively low, so the cost of labor resettlement is relatively low. At the same time, most mining areas in GS, YN and QH and some mining areas in SHX have great mining difficulties and relatively old equipment level, so the loss of fixed assets in the process of overcapacity reduction is relatively low. The comparison between the BOAS and SOAS also effectively reduces the total cost of capacity reduction. The total cost of the BOAS is reduced by 20 billion yuan and 5.93% compared with the SOAS. Among them, asset losses were reduced by 7 billion yuan, and labor resettlement costs were saved by 12 billion yuan.

The smooth and proper distribution of labor resettlement is the basic premise for an overcapacity reduction. The total cost of labor resettlement in the GAS is 147 billion yuan in Table 3. According to the special funds allocated by the central government and the proportion of labor resettlement estimated by the Ministry of Social Affairs, about 72 billion yuan will be used for labor resettlement in the coal industry, with a funding gap of 75 billion yuan. In contrast, the BOAS has a funding gap of only 48 billion yuan, reducing the gap by 37%. In order to further compare and analyze the differences in labor resettlement costs among the BOAS, the GAS and the SOAS, we plotted the distribution of labor resettlement costs in each province under the three allocation schemes (shown as Figure 5. (a), (b), and (c)). As shown here, there are only 2 provinces (SD and SX) with a total labor resettlement cost of more than 10 billion yuan based on the BOAS, and 7 provinces with labor resettlement cost between 5 billion yuan and 10 billion yuan; However, based on the GAS, there are 5 provinces (SD, SX, HN, HB, and GZ) with resettlement costs exceeding 10 billion yuan, 6 provinces between 5 billion yuan and 10 billion yuan. Meanwhile, there are three provinces (SX, SD and HN) more than 10 billion people based on the SOAS. Thus, compared with the GAS and the SOAS, the cost of labor resettlement based on the BOAS is not only significantly lower in total, but also means fewer provinces with higher labor resettlement cost. As the provinces with higher labor resettlement costs also have higher overcapacity reduction, reducing the labor resettlement costs in these provinces will undoubtedly help to reduce the personnel resistance, and ultimately promote the smooth progress of coal overcapacity reduction in China.

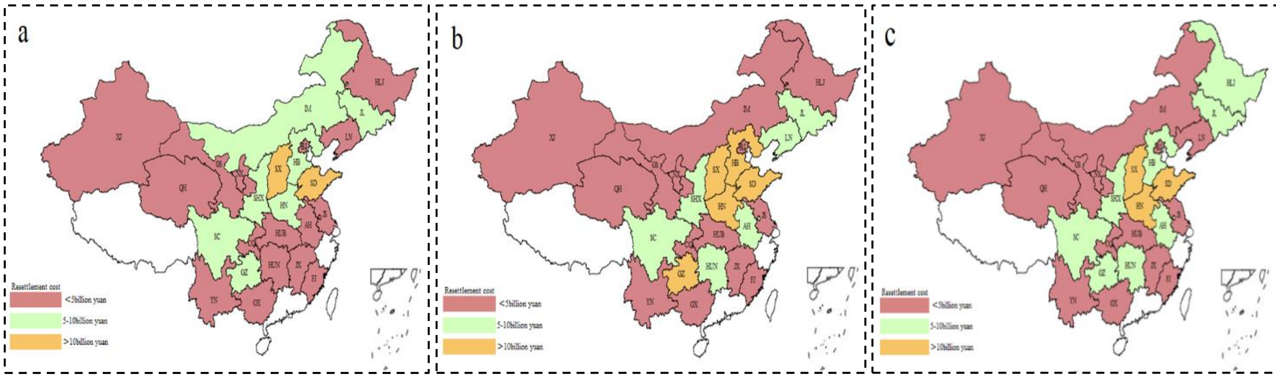


**Figure 5. (a)** Labor resettlement cost based on BOAS**; (b)** Labor resettlement cost based on GAS**; (c)** Labor resettlement cost based on SOAS

*4.2.2. Comparative analysis of TFP growth rates*

By comparing the BOAS, the GAS and the SOAS, the growth rate of $\dot{TFP}$ of the BOAS has been significantly increased. As shown in Table 3**,** the growth rate of $\dot{TFP}$ of the BOAS is 2.14% and 0.60% higher than that of the GAS and the SOAS, respectively. This is mainly since the BOAS has greatly reduced the overcapacity reduction in HB, SX, HN and XJ and other regions to production tasks. These are China's coal-rich provinces and through many years of production and operation have accumulated relatively rich experience in technology and management, and in complex conditions of mining technology. They are also equipped with specialized knowledge of human resources (e.g., HN, SX and HB). The extraction time is shorter but has good mining conditions and the advanced equipment and technology (e.g. XJ). By reducing these provinces' overcapacity reduction tasks, they can maximize their technological and managerial advantages, thus promoting the growth of industry total factor productivity.

*4.2.3. Comparative analysis of environmental benefits*

Compared with the GAS and the SOAS, the environmental benefits of the BOAS have been significantly improved. It can be seen in Table 3 that the environmental benefits of the BOAS are 73 billion yuan and 71 billion yuan higher than those of the GAS and the SOAS, respectively. As shown in Figure 6, compared with the GAS, there are seven provinces with improved environmental benefits in the mining area based on the BOAS, which are IM, SHX, GS, YN, QH, HUB and JS. Among them, IM has the biggest improvement in environmental benefits, far surpassing other provinces and regions. Compared with the SOAS, there are 10 provinces and regions based on BOAS, which are LN, FJ, HUB, IM, GX, GZ, YN, SHX, GS and QH. Among them, IM has the biggest improvement in environmental benefits, far surpassing other provinces and regions. The main reason is that the cost gap of the three wastes pollution control in the mining area is not big, so the environmental benefit of the mining area is related to the scale of the withdrawal capacity of the provinces and regions, and the unit cost of overcapacity reduction in IM is the second lowest among the 25 provinces, so the withdrawal capacity scale of Inner Mongolia is greater, and the improvement of the environmental benefit of the mining area is the most transparent. In addition, the environmental benefits of the remaining 18 provinces under the three allocation schemes are not significantly different, but the cumulative environmental benefits of the BOAS are significantly improved.

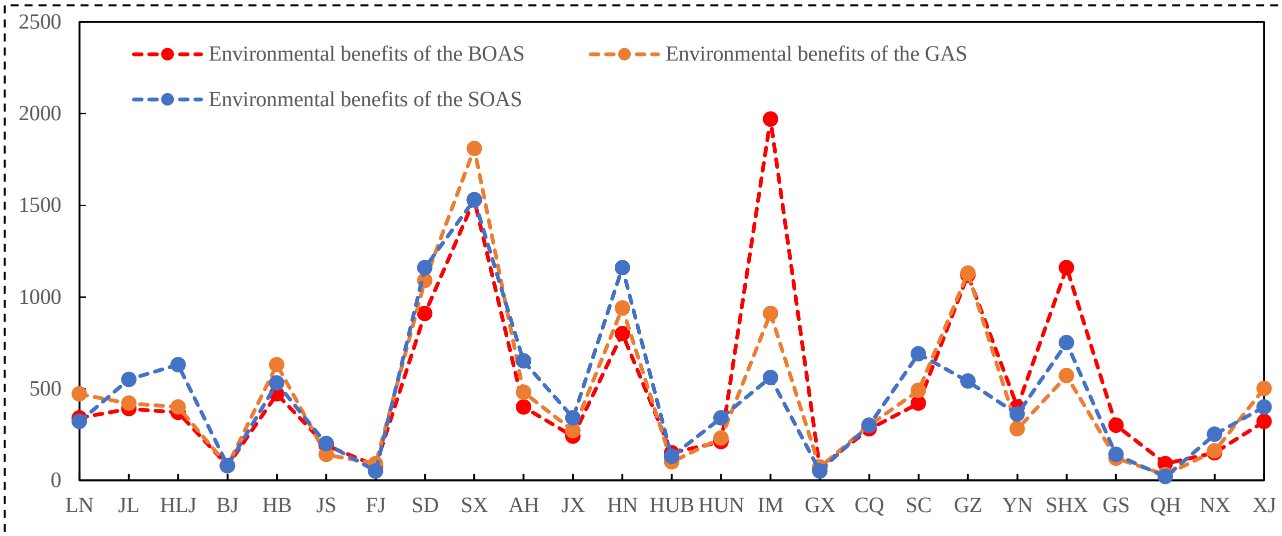


**Figure 6.** Comparison of environmental benefits of BOAS, GAS, SOAS

### *4.2.4. Comparative analysis of fairness of coal de-capacity*

In order to examine the provincial fairness of the BOAS, this study applies the Gini coefficient as a measure. This approach is widely used in the analysis of other distribution problems and degrees of equilibrium. Generally speaking, a Gini coefficient of less than 0.2 represents an absolute distribution average, 0.2–0.3 represents a relatively average distribution, 0.3–0.4 represents a relatively reasonable distribution, 0.4–0.5 represents a large gap, and greater than 0.5 represents a wide disparity in distribution. The calculation methods of the Gini coefficient mainly include the direct calculation, curve fitting, grouping calculation, and decomposition calculation approaches.

Taking into account the characteristics of coal de-capacity data in different provinces, we use the fitting curve method in this study to calculate the Gini coefficient. The basic idea is to use mathematical methods to fit the Lorenz curve, obtain the function expression of the curve, use the integral method to calculate the area, and then obtain the Gini coefficient. The specific steps are as follows: First, set the function of the Lorenz curve as the power function $I=\alpha P^{\beta}$ and obtain the parameters of the Lorenz curve by the regression method according to the selected sample data, that is, $I=\hat{\alpha}P^{\hat{\beta}}$; then use the integral method to calculate the area: $S_B=\int_0^1 \hat{\alpha}P^{\hat{\beta}}dP=\hat{\alpha}/(\hat{\beta}+1)$; finally, calculate the Gini coefficient: $G=\frac{S_A}{S_{A+B}}=\frac{S_{A+B}-S_B}{S_{A+B}}=1-\frac{2\hat{\alpha}}{\hat{\beta}+1}$. The calculation results are shown in Table 4. In this study, taking the de-capacity cost per capita and reduction scale per capita as the order basis of the Lorenz curve, and taking the cumulative percentage of employees and of cumulative percentage of de-capacity costs (or reduction scales) as the horizontal and vertical coordinates, respectively, we get the Lorenz curve of the BOAS, the GAS and the SOAS. Results are shown as Figure 7 and Figure 8.

According to Table 4, Figures 7 and 8, when the Lorentz curve is drawn according to the order of per capita production cost, the Gini coefficient of the GAS is less than 0.2, which belongs to the absolute average category, while the Gini coefficient of the BOAS and the SOAS is slightly higher than 0.2, which belongs to the comparatively average category. The Gini coefficients of the three schemes are in the range of 0.2-0.3 when the Lorentz curve is drawn according to the ranking of per capita capacity exit scale, which belongs to the comparative average category. Therefore, the BOAS proposed in this paper not only improves the growth rate, improves the environmental benefits of mining areas and reduces the cost of overcapacity reduction, but it also has a high degree of fairness.

**Table 4** Gini coefficient calculation results

| Lorenz curve sorting basis | De-capacity scheme | Gini coefficient |
|---|---|---|
| De-capacity cost per capita | BOAS | 0.211 |
| | GAS | 0.183 |
| | SOAS | 0.207 |
| Reduction scale per capita | BOAS | 0.294 |
| | GAS | 0.228 |
| | SOAS | 0.221 |

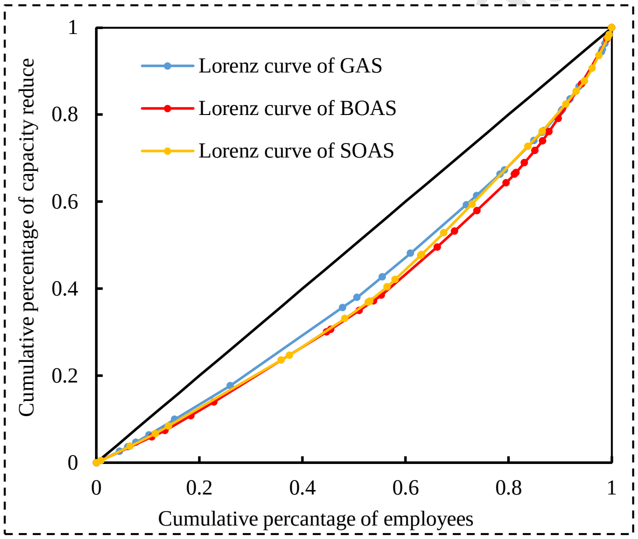


**Figure 7.** Lorenz curves based on de-capacity cost per capita

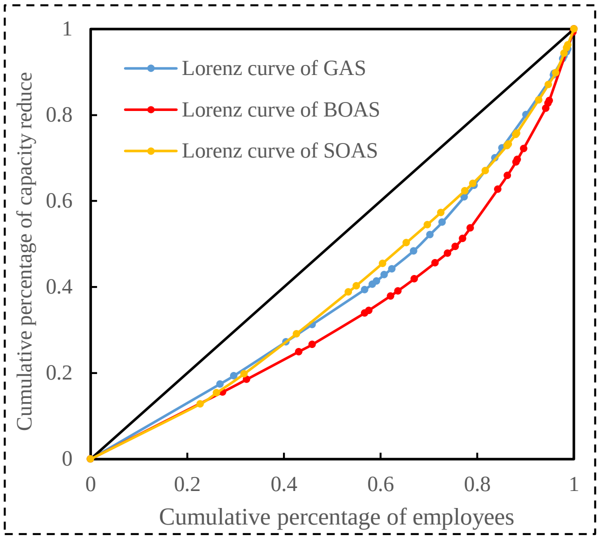


**Figure 8.** Lorenz curves based on reduction scale per capita

### 4.3. Scenario Analysis

In the analysis above, we set different preferences for the two goals of growth rate of TFP and environmental benefit maximization of mining areas, which means that when formulating the allocation scheme of overcapacity reduction, we believe that economic quality factors are more important than environmental quality factors. However, in the actual process of policy formulation, the central government will have different target preferences due to some practical reasons or considering the future development direction. For example, in the case of ecological protection and increasing pressure to respond to climate change, the central government may give priority to environmental benefits and choose environmental quality-oriented policies; while in the case of weak ecological environment constraints, it may give priority to the quality of industrial development, thus tending to economic quality-oriented policy scheme. It is necessary to further analyze the quota allocation schemes of overcapacity reduction under different government preferences. Therefore, we set the preference weights to analyze the allocation scheme in the environment quality-oriented scenario. The weights are as follows: $[\lambda_1, \lambda_2]=[0.3, 0.7]$. At the same time, we set the preference weights to analyze the allocation scheme in the same preference-oriented scenario. The weights are as follows: $[\lambda_1, \lambda_2]=[0.5, 0.5]$. The calculation results are shown in Table 5, Figure 9, and Figure 10 reflecting the optimal allocation proportion of the total target of coal overcapacity reduction in each province under different weight combinations and the implementation rate of each province's capacity reduction policy under different weight combinations. Overall, Table 5 shows that in the context of a quality-oriented environment, environmental benefits and total cost of overcapacity reduction increase relatively, while the growth rate of TFP decreases relatively. In the quality-oriented economic situation, environmental benefits and overcapacity reduction costs are relatively reduced, while the growth rate of TFP is relatively increased. Specifically, compared with the same preference-oriented scenario, the environmental benefits of overcapacity reduction under the environmental quality-oriented allocation scheme increase by 11 billion yuan, while the growth rate of TFP decrease by 0.32%. Compared with the same preference-oriented scenario, the environmental benefits under the economic-quality-oriented allocation scheme decrease by 8 billion yuan, while the growth rate of TFP increase by 0.44%. This indicates that different allocation schemes can be obtained by solving the model under different preference scenarios, and the membership weight is large, that is, the preferred target performs better, and the inherent consistency of the model is established.

**Table 5** Coal de-capacity allocation among provinces of different weights

| Province | Environmental quality preferences | | | | Same preference | | | | Economic quality preferences | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\dot{TFP}$ =7.16%， $C_e$ =12630, $TC$ =3324.718 | | | | $\dot{TFP}$ =7.48%， $C_e$ =12520, $TC$ =3220.954 | | | | $\dot{TFP}$ =7.92%， $C_e$ =12440, $TC$ =3126.201 | | | |
| | Reduction scale | Allocation ratio | Reduction proportion | Execution rate | Reduction scale | Allocation ratio | Reduction proportion | Execution rate | Reduction scale | Allocation ratio | Reduction proportion | Execution rate |
| LN | 1757.610 | 2.197% | 25.030% | 89.820% | 1958.819 | 2.448% | 26.350% | 95.030% | 2210.783 | 2.763% | 27.460% | 102.920% |
| JL | 2058.994 | 2.574% | 38.780% | 80.530% | 2248.657 | 2.811% | 41.460% | 82.260% | 2493.749 | 3.117% | 45.560% | 83.060% |
| HLJ | 2170.164 | 2.713% | 27.640% | 74.410% | 2239.986 | 2.800% | 28.830% | 73.610% | 2365.098 | 2.956% | 29.430% | 76.150% |
| BJ | 520.000 | 0.650% | 100.000% | 100.000% | 520.000 | 0.650% | 100.000% | 100.000% | 520.000 | 0.650% | 100.000% | 100.000% |
| HB | 2627.903 | 3.285% | 26.720% | 79.780% | 2781.418 | 3.477% | 27.880% | 80.940% | 2998.955 | 3.749% | 29.410% | 82.750% |
| JS | 1187.317 | 1.484% | 48.710% | 98.770% | 1191.957 | 1.490% | 46.950% | 102.780% | 1212.805 | 1.516% | 45.630% | 107.610% |
| FJ | 454.806 | 0.569% | 19.910% | 106.590% | 465.243 | 0.582% | 19.130% | 113.220% | 502.345 | 0.628% | 19.040% | 122.820% |
| SD | 5463.103 | 6.829% | 37.690% | 84.840% | 5692.170 | 7.115% | 38.030% | 87.620% | 5832.610 | 7.291% | 38.580% | 88.490% |
| SX | 10087.653 | 12.609% | 9.160% | 76.610% | 9920.900 | 12.401% | 8.250% | 83.680% | 9893.000 | 12.366% | 8.170% | 84.250% |
| AH | 2181.528 | 2.727% | 16.230% | 73.080% | 2338.464 | 2.923% | 17.310% | 73.440% | 2553.278 | 3.192% | 17.740% | 78.250% |
| JX | 1424.850 | 1.781% | 47.120% | 81.960% | 1454.934 | 1.819% | 48.560% | 81.150% | 1526.645 | 1.908% | 49.550% | 83.500% |
| HN | 5378.779 | 6.723% | 34.830% | 83.120% | 5213.241 | 6.516% | 34.610% | 81.060% | 5149.949 | 6.437% | 34.090% | 81.320% |
| HUB | 882.232 | 1.103% | 46.020% | 85.680% | 910.354 | 1.138% | 44.980% | 90.350% | 952.159 | 1.190% | 44.530% | 95.450% |
| HUN | 1216.459 | 1.521% | 30.080% | 76.950% | 1262.970 | 1.579% | 31.080% | 77.270% | 1349.013 | 1.686% | 33.010% | 77.710% |
| IM | 10957.640 | 13.697% | 5.960% | 138.330% | 11830.863 | 14.788% | 5.710% | 156.000% | 12713.470 | 15.892% | 5.250% | 182.200% |
| GX | 456.858 | 0.571% | 40.890% | 109.550% | 449.578 | 0.562% | 38.420% | 114.720% | 440.485 | 0.551% | 37.650% | 114.970% |
| CQ | 1912.505 | 2.391% | 40.770% | 91.320% | 1833.145 | 2.291% | 40.120% | 88.950% | 1802.513 | 2.253% | 39.960% | 87.850% |
| SC | 2836.449 | 3.546% | 25.270% | 85.660% | 2729.265 | 3.412% | 25.940% | 80.280% | 2684.263 | 3.355% | 26.960% | 75.980% |
| GZ | 8059.138 | 10.074% | 19.630% | 129.580% | 7662.395 | 9.578% | 16.040% | 150.820% | 7208.803 | 9.011% | 15.920% | 142.990% |
| YN | 2684.062 | 3.355% | 26.070% | 98.410% | 2628.107 | 3.285% | 26.130% | 96.120% | 2592.380 | 3.240% | 25.910% | 95.640% |
| SHX | 9113.954 | 11.392% | 12.230% | 112.670% | 8417.345 | 10.522% | 11.830% | 107.580% | 7473.435 | 9.342% | 10.320% | 109.520% |
| GS | 2143.324 | 2.679% | 16.090% | 120.950% | 2098.294 | 2.623% | 14.320% | 133.040% | 1924.817 | 2.406% | 13.610% | 128.520% |
| QH | 708.625 | 0.886% | 14.680% | 133.760% | 628.293 | 0.785% | 12.130% | 143.280% | 576.256 | 0.720% | 9.650% | 165.400% |
| NX | 810.477 | 1.013% | 7.100% | 78.980% | 870.152 | 1.088% | 8.040% | 74.910% | 964.023 | 1.205% | 9.050% | 73.760% |
| XJ | 2906.498 | 3.633% | 9.940% | 89.170% | 2654.293 | 3.318% | 8.740% | 92.540% | 2059.834 | 2.575% | 7.540% | 83.300% |
| Country | 80000.926 | 100.000% | 13.950% | | 80000.840 | 100.000% | 13.950% | | 80000.665 | 100.000% | 13.950% | |

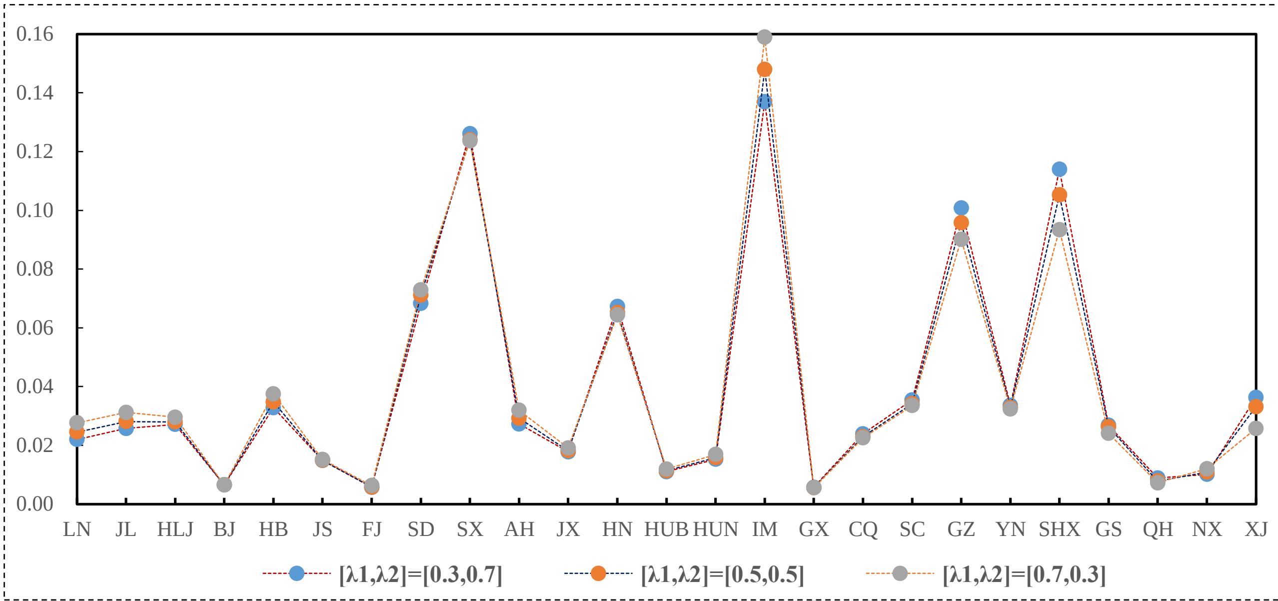


**Figure 9.** The optimal allocation ratio of total coal de-capacity in each province under different weight combinations

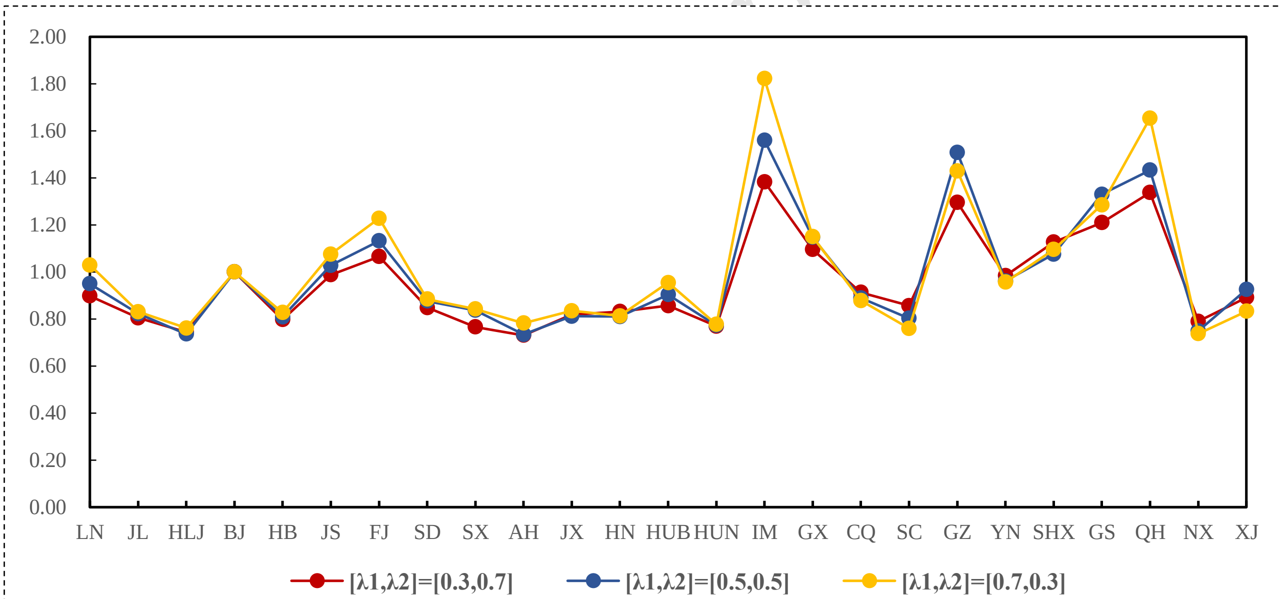


**Figure 10.** Execution rate of de-capacity policies in each province under different weight combinations

## 5. Conclusions and implications

### 5.1. Key conclusions

In view of the urgency of China's coal industry's de-capacity and the fundamental requirements of "reducing quantity and improving quality," and the environmental protection of mining areas, construct a provincial allocation model of coal overcapacity reduction in China based on bi-level multi-objective non-linearity. In the model, we take the growth rate of TFP in China's coal industry and the maximum environmental benefit in mining areas as the upper objective, and take the minimum total cost of overcapacity reduction as the lower objective. The BOAS for 25 coal-producing provinces and regions are obtained. In order to verify the rationality of the BOAS, we compare the results of BOAS with those of the GAS and the SOAS e from four aspects: cost, growth rate, environmental benefit and degree of fairness of the mining area. On this basis, through the scenario analysis, the changed rules of the target value and allocation scheme under different preferences of the central government are investigated. The main conclusions are as follows:

- Some local governments have a low degree of willingness to implement the central government's policy of overcapacity reduction, while some local governments have a high degree of enthusiasm for the policy, which exceeds the central government's expectation. The heterogeneity is consistent with the actual situation of China's overcapacity reduction. HLJ, AH, HUN, SC and NX with the lowest policy implementation rates were 76.15%, 78.25%, 77.71%, 75.98% and 73.76%, respectively. In these provinces, the cost of capacity reduction is high or economic development is relatively backward, so they are passive in capacity reduction due to the huge financial pressure. FJ, IM, GZ, GS and QH with high policy implementation rates were 122.82%, 182.20%, 142.99%, 128.52% and 165.40%, respectively. These provinces are rich in coal resources and positive about implementing de-capacity tasks, playing an important role in successfully solving the problem of overcapacity in the Chinese coal industry.
- Compared with the GAS and the SOAS, the BOAS has lower total cost of coal overcapacity reduction, larger growth of TFP, better environmental benefits in the mining area, and more fairness, which can better balance efficiency, cost, environment, and fairness. To be specific, the total cost of the BOAS is 64 billion yuan and 20 billion yuan lower than that of the GAS and the SOAS, respectively. At the same time, the TFP growth of the BOAS is 2.14% and 0.60% higher than that of the GAS and the SOAS, respectively. The environmental benefit of the BOAS is 73 billion yuan higher than that of the GAS and 71 billion yuan higher than that of the SOAS. In addition, although the Gini coefficients calculated by different indicators are different, the Gini coefficient of the BOAS is less than 0.3, which belongs to the absolute or relative fairness category.
- Although there are some differences in quota allocation schemes of coal overcapacity reduction under different situations, the trend of change is consistent with the actual situation, indicating that the model has good internal consistency and can be a valid reference for the government to formulate policies under different situations. Specifically, under the environment-oriented situation, provinces with larger growth rate of environmental

benefit of capacity reduction and lower unit capacity withdrawal cost, allocated more capacity, while provinces with smaller growth rate of environmental benefit and higher unit capacity withdrawal cost, allocated less capacity. Under the quality-oriented situation, provinces with larger growth rate of TFP and lower unit withdrawal cost allocated more capacity reduction, while provinces with smaller growth rate of TFP and higher unit withdrawal cost allocated less capacity reduction.

### 5.2. Policy implications

Based on the above conclusions, the following suggestions are put forward to promote the smooth completion of coal capacity reduction in China and promote the supply-side structural reform of the coal industry.

- There is a large gap in the willingness of different to execute de-capacity among provinces. For example, the implementation rate in IM and GZ is far more than 100%, while that in HLJ and AH is no more than 80%. Therefore, the central government could establish a market system for trans-provincial de-capacity quotas transactions and ensure a reasonable price mechanism, such as a capacity permit trading scheme (Shi et al., 2019), which may change the way of de-capacity from "forced push" by the government to "active retreat" of enterprises. Specifically, providing a public auction trading platform between the provinces with low de-capacity cost and high implementation rate and the provinces with high cost and low implementation rate, realizing market-oriented independent transactions of de-capacity quotas. In this way, not only the total cost of de-capacity could be reduced and local fiscal pressure could be eased, but also the external benefits from the survival of the inferior product could be obtained. The Chinese coal industry will be "slimmer" and "healthier" ultimately.
- There are some differences in the allocation schemes with different policy preferences. The government should balance efficiency and environmental protection according to the current actual situation and budget constraints to formulate a coal de-capacity quota allocation scheme suitable for the current development. When environmental constraints in mining areas are very strong, the government can give priority to the quality-oriented allocation scheme to alleviate environmental pressure, and to ensure the smooth exit of excess capacity. When environmental constraints in mining areas are not strong, the government can give priority to the economic quality-oriented allocation scheme in order to achieve the "quality improvement" requirement of coal capacity reduction, which will then truly improve the quality and efficiency of the coal industry.
- Due to the unbalanced development of China's provinces, there is a certain heterogeneity in financial

commitment and environmental constraints. When formulating the task of coal capacity reduction in each province, the central government should fully consider these differences and change the way of "one size fits all" to "customized management". Specifically, the central government should not only take environmental benefits and industry development quality into consideration from a global industry perspective, but also weigh the de-capacity cost tolerance of each province from the perspective of local interests, so as to develop a customized de-capacity allocation scheme that balancing efficiency, cost, environment and fairness, reduce the local financial burden, improve the enthusiasm of local governments for de-capacity, and ultimately achieve efficient and smooth exit of excess capacity of China's coal industry. Moreover, the same principle applies to the other industries with wide geographical distribution of overcapacity management, such as the steel industry.

### 5.3. Outlook

In this paper, we quantitatively study the provincial allocation of coal de-capacity targets in China and propose some useful policies. However, there are still some meaningful problems remained to be further explored. First, compared with how to allocate de-capacity, it is also important to know how to achieve the local target of coal output reduction in practice. Thus, it is necessary to further study how the local government assigns the given quotas to coal enterprises. Second, the effect of de-capacity is partly reflected in the results of the tripartite game among the central government, local governments and coal enterprises. Therefore, the tripartite dynamic game relationships should be discussed to figure out the predicament and countermeasures of overcapacity governance in China's coal industry.

**Acknowledgments**

This research is supported by the National Natural Science Foundation of China (No. 71573252; No. 71828401), Social Science Foundation of Jiangsu Province (No. 18JD014), and the Think Tank of Energy Mining Economy (2018 Project for Cultural Evolution and Creation of CUMT 2018WHCC01).

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**Author Statement**

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# Highlights

- A novel allocation model based on bi-level multi-objective optimization is constructed.
- The environmental benefit is incorporated into government's de-capacity target appeal.
- Optimal scheme is more efficient, environment-friendly, and cost-effective than the others.
- The execution rate of each province for assigned de-capacity task is quite different.
- The optimal allocation ratio of coal de-capacity in different scenarios is proposed.

**Appendix A.** *Estimation of Coal Boundary Production Function for provinces*

The boundary production function is a common method used to estimate potential output and technical efficiency. This method, based on economic growth theory, can reveal the relationship between inputs and outputs, and is widely used in various production management fields. In this study, therefore, the boundary production function is adopted to measure the coal capacity and capacity utilization rate for each province. The main steps are as follows. First, the appropriate production function form is determined and the average production function equation is estimated using the ordinary least squares (OLS) method. Second, the average production function equation estimated above is shifted upward until the residual value is less than or equal to zero; that is, the boundary production function is obtained by taking the maximum residual value estimated by OLS and adding it to the constant term of the average production function. Finally, the coal capacities of different provinces are calculated, based on the estimated boundary production function.

In this study, the boundary production function is set as the widely used Cobb-Douglas production function. Its basic form is:

$$Y = A \times K^{\alpha} \times L^{\beta} \times e^{-u} \qquad (u \geq 0) \tag{A.1}$$

where $Y$ is actual output, $K$ is capital input, and $L$ is labor input. $A$ is technological level, $\alpha$ and $\beta$ are the respective output elasticities of capital and labor, and $e^{-u}$ is production inefficiency. Taking the logarithms of both sides of equation (1), we get:

$$\ln Y = \ln A + \alpha \ln K + \beta \ln L - u \tag{A.2}$$

Let $\ln A = \lambda$ and $E(u) = \delta$, and formula (2) can be rewritten as:

$$\ln Y = (\lambda - \delta) + \alpha \ln K + \beta \ln L - (u - \delta) \tag{A.3}$$

As $E(u - \delta) = 0$, the OLS method is used to estimate parameters, and we then get the average production function as follows:

$$\ln \bar{Y} = \varepsilon + \hat{\alpha} \ln K + \hat{\beta} \ln L \tag{A.4}$$

where $\varepsilon = \lambda - \hat{\delta}$. According to the property that all actual output is below the boundary production function, the maximum residual value $\hat{\delta}$ can be further obtained as:

$$\max(\ln Y - \ln \bar{Y}) = \max\{(\lambda + \alpha \ln K + \beta \ln L - u) - (\varepsilon + \hat{\alpha} \ln K + \hat{\beta} \ln L)\} \tag{A.5}$$

We get the value of $\hat{\lambda}$ by incorporating $\hat{\delta}$ into formula (4). Therefore, the estimated boundary production function is:

$$Y^{*} = e^{\hat{\lambda}} \cdot K^{\hat{\alpha}} \cdot L^{\hat{\beta}} \tag{A.6}$$

where $Y^*$ is coal capacity. Finally, the coal capacity utilization rate $CU$ is:

$$CU = Y/Y^* \tag{A.7}$$

## Appendix B. *Estimation of coal de-capacity cost for provinces*

According to the theory of production factors, the coal de-capacity cost includes two main components: the disposal cost of fixed assets and labor resettlement cost. Due to the particularity of coal mine production and its geographical environments, most assets of the coal industry are fixed in underground engineering and machinery equipment. In addition, the production equipment and facilities of coal mines are rather specialized and have limited uses. Therefore, after a mine closure, it is difficult to transfer the original assets to other industries, resulting in most or all losses of asset value. Further, China's coal industry still belongs to the labor-intensive form industry[9], and the closure of mines will inevitably lead to massive unemployment and large labor resettlement costs. Therefore, in this study, we mainly consider the disposal cost of fixed assets and labor resettlement cost.

*(1)Disposal cost of fixed assets*

Considering the particularity of asset disposal in the process of coal de-capacity, in this study we use the net residual value, which is the expected proceeds from the sale of an asset at the end of its estimated useful life, to measure the recoverable amount of fixed assets. The calculation formula is as follows:

$$r = K_u \times (1 - R_r) / K \tag{B.1}$$

where $r$ is the asset loss rate of fixed assets, $K_u$ represents the original fixed assets of the coal industry, and $R_r$ is the salvage rate of fixed assets.

*(2) Labor resettlement cost*

At present, research concerning labor resettlement costs in coal de-capacity is mainly based on qualitative analysis. In this study, taking into account national relevant laws and regulations and the labor resettlement policies of 25 coal-producing provinces, we divide the labor resettlement cost of coal de-capacity into four parts: daily living (including housing), social security, employment, and education costs. The cost is calculated for one year and the specific estimation method is shown in **Table A**.

**Table A** Estimation method of labor resettlement cost

| Cost type | Basic meaning | Estimation formula |
| --- | --- | --- |

[9] In 2012, for example, the coal output in United States was 1 billion tons and coal industry workers numbered about 100,000 people. In the same year, the coal output in China was 3.65 billion tons, and coal industry workers numbered about 5.25 million people. That is to say, China's coal output is 3.6 times that of the United States, but the number of its industry workers is 52.5 times of that of the United States.

| | | |
|---|---|---|
| Daily living cost ( $C_1$ ) | Refers to the cost of maintaining a normal life during the period of unemployment caused by coal de-capacity; mainly includes some basic expenses, such as diet, clothing, medical care, transportation, and residence cost. | $C_1 = P_u$<br>$C_1$ is the per capita daily living cost, while $P_u$ is the per capita consumption expenditure of residents in coal provinces. |
| Social security cost ( $C_2$ ) | Refers to the cost of ensuring that people affected by the de-capacity can still enjoy basic pension, medical, and other social insurance in the process of temporary unemployment. | $C_2 = S_u \times 36.75\%$<br>$C_2$ is the per capita social security cost, $S_u$ is the average annual salary of coal industry employees in coal provinces, and 36.75% is the current general rate of "Five-insurance," referring to endowment insurance, medical insurance, unemployment insurance, industrial injury insurance, and maternity insurance. |
| Employment cost ( $C_3$ ) | Refers to the investment cost for jobs, that is, the amount of investment needed to add a new job. | $C_3 = (K_{总} / L_a) \times (L_w / L_a)$<br>$C_3$ is the per capita employment cost, $K_{总}$ is the gross investment in fixed assets in coal provinces, $L_w$ is the number of employees in coal provinces, and $L_a$ is the number of economical active people in these provinces. |
| Education cost ( $C_4$ ) | Refers to the education investment needed to find a new job for people affected by coal de-capacity. | $C_4 = (I_b / L_b)(N_m - N_n)$<br>$C_4$ is the per capita education cost, $I_b$ is the education investment in coal provinces, $L_b$ is the total number of educated people in coal provinces, $N_m$ is the minimum level of labor skills required for reemployment in coal provinces, and $N_n$ is the labor skill level of the unemployed workers in coal de-capacity in coal provinces. |
| Total labor resettlement cost | $w = C_1 + C_2 + C_3 + C_4$ | |

*(3) Estimation of total cost of coal de-capacity*

Based on the analysis above, the total cost of de-capacity, including the disposal cost of fixed assets and labor resettlement cost, is given by:

$$C(r, w, \Delta Y^*) = r\Delta K + w\Delta L = r(K_s - K_e) + w(L_s - L_e) \quad \text{(B.2)}$$

where $C(*)$ is the total cost of coal de-capacity, $r$ and $w$ are the respective release prices of capital and labor, i.e., the asset loss rates of fixed assets and per capita labor resettlement costs. According to the estimated boundary production function, $\Delta Y^* = Y_s^* - Y_e^* = Y_s^* - e^{\hat{\lambda}} K_e^{\hat{\alpha}} L_e^{\hat{\beta}}$. $Y_s^*$, $K_s$, and $L_s$ are the estimated capacity, capital, and labor inputs of coal industry in 2020 without the implementation of coal de-capacity. $Y_e^*$, $K_e$, and $L_e$ are the estimated capacity, capital, and labor inputs of the coal industry in 2020 under the condition of achieving the target of de-capacity. Therefore, the problem of cost minimization of de-capacity can be expressed as:

$$\begin{aligned} & C(r, w, \Delta Y^*) = \min_{\Delta K, \Delta L}(r\Delta K + w\Delta L) = \min_{K_e, L_e}\left[r(K_s - K_e) + w(L_s - L_e)\right] \\ & s.t. \quad \Delta Y^* = Y_s^* - e^{\hat{\lambda}} K_e^{\hat{\alpha}} L_e^{\hat{\beta}} \end{aligned} \quad \text{(B.3)}$$

By constructing the Lagrange function, we can obtain the conditional factor release function of capital $K_e$ and labor $L_e$, that is:

$$K_e\left(r,w,\Delta Y^*\right)=\left[\left(Y_s^*-\Delta Y^*\right)e^{-\hat{\lambda}}\left(\frac{\hat{\alpha}w}{\hat{\beta}r}\right)^{\hat{\beta}}\right]^{\frac{1}{\hat{\alpha}+\hat{\beta}}} \tag{B.4}$$

$$L_e\left(r,w,\Delta Y^*\right)=\left[\left(Y_s^*-\Delta Y^*\right)e^{-\hat{\lambda}}\left(\frac{\hat{\alpha}w}{\hat{\beta}r}\right)^{-\hat{\alpha}}\right]^{\frac{1}{\hat{\alpha}+\hat{\beta}}} \tag{B.5}$$

Therefore, we can get the total cost function of de-capacity in the provinces:

$$C\left(r,w,\Delta Y^*\right)=r\left\{K_s-\left[\left(Y_s^*-\Delta Y^*\right)e^{-\hat{\lambda}}\left(\hat{\alpha}w/\hat{\beta}r\right)^{\hat{\beta}}\right]^{1/(\hat{\alpha}+\hat{\beta})}\right\}+w\left\{L_s-\left[\left(Y_s^*-\Delta Y^*\right)e^{-\hat{\lambda}}\left(\hat{\alpha}w/\hat{\beta}r\right)^{-\hat{\alpha}}\right]^{1/(\hat{\alpha}+\hat{\beta})}\right\} \tag{B.6}$$

**Appendix C.** *Calculation of TFP growth for provinces, based on Solow's residual value method*

As an important index to measure the quality of economic growth, TFP can truly reflect the efficiency of the transformation of overall economic input into output. Therefore, it is necessary to introduce the concept of TFP in the coal de-capacity allocation model. Based on the comprehensive consideration of data availability, applicability, and algorithm consistency, in this study we use the Solow residual method in the form of a two-factor Cobb-Douglas production function to calculate the TFP growth rate. The basic idea is that the average production function is estimated first; the residual error is then calculated by deducting the growth rate of each input factor from the output growth rate, which can be used to estimate the TFP growth rate for the provinces. The steps are as follows.

According to the estimation result of **Appendix A**, the average production function of the coal industry is $\ln\overline{Y}=\varepsilon+\hat{\alpha}\ln K+\hat{\beta}\ln L$, so the production function at time $t$ is:

$$Y_t=e^{\varepsilon_t}\times K_t^{\hat{\alpha}}\times L_t^{\hat{\beta}} \tag{C.1}$$

where $Y_t$, $K_t$, and $L_t$ are the actual output, capital input, and labor input at time $t$. Taking the derivative of both sides of this equation with respect to $t$ and dividing both sides by $Y$, we get:

$$\frac{1}{Y}\frac{dY}{dt}=\frac{1}{e^{\varepsilon}}\frac{d(e^{\varepsilon})}{dt}+\hat{\alpha}\frac{1}{K}\frac{dK}{dt}+\hat{\beta}\frac{1}{L}\frac{dL}{dt} \tag{C.2}$$

Since the presupposition of Solow's residual method is constant returns to scale, it is necessary to normalize the elastic coefficient of production factors; therefore we let:

$$\alpha=\frac{\hat{\alpha}}{\hat{\alpha}+\hat{\beta}}\,,\quad \beta=\frac{\hat{\beta}}{\hat{\alpha}+\hat{\beta}}$$

Then $\alpha+\beta=1$ and the TFP growth rate $T\dot{F}P$ is:

$$T\dot{F}P=\frac{1}{e^{\varepsilon}}\frac{d(e^{\varepsilon})}{dt}=\frac{1}{Y}\frac{dY}{dt}-\alpha\frac{1}{K}\frac{dK}{dt}-\beta\frac{1}{} \tag{C.3}$$

Combined with the actual situation of the coal industry, the TFP growth rate before and after the coal de-capacity (i.e., the TFP growth rate between 2020 and 2015) is:

$$T\dot{F}P = \frac{Y_e - Y_o}{Y_o} - \alpha\frac{K_e - K_o}{K_o} - \beta\frac{L_e - L_o}{L_o} \tag{C.4}$$

where $Y_o$, $K_o$, and $L_o$ are the actual output, capital input, and labor input. $Y_e$ is the expected coal output in 2020 under the condition of achieving the target of de-capacity. Taking formulas (B.4) and (B.5) into the formula above, we obtain the final formula for the TFP growth rate:

$$T\dot{F}P = \frac{Y_e - Y_o}{Y_o} - \alpha\left\{\left[\left(Y_s^* - \Delta Y^*\right)e^{-\hat{\lambda}}\left(\frac{\hat{\alpha}w}{\hat{\beta}r}\right)^{\beta}\right]^{\frac{1}{\alpha+\beta}} - K_o\right\}\Bigg/K_o - \beta\left\{\left[\left(Y_s^* - \Delta Y^*\right)e^{-\hat{\lambda}}\left(\frac{\hat{\alpha}w}{\hat{\beta}r}\right)^{-\alpha}\right]^{\frac{1}{\alpha+\beta}} - L_o\right\}\Bigg/L_o \tag{C.5}$$