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A decision-making model for efficient fair electricity rationing under major power outrage emergencies

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Abstract

Major power outages emergencies (MPOEs) are increasingly occurring with greater frequency and wreaking havoc, necessitating the effective decision-making for electricity rationing to mitigate economic losses incurred and maintain social stability. To address this issue, this paper proposes an efficient fair electricity rationing decision-making model under MPOEs, including two methods to quantify the efficiency and fairness of the electricity rationing. Firstly, the inoperability input-output model is employed to quantify the efficiency by assessing the business interruption costs caused by MPOEs. Secondly, the fairness is quantified by the fairness perception of the affected regions, which consider their bounded rational comparisons based on the Prospect theory. Then, the NSGA-II is utilized to solve the model. Finally, Sichuan MPOE in 2022 is designed as a numerical experiment to validate the proposed model, accompanied by corresponding discussions to demonstrate the impact of "supercities" on electricity rationing and the significance of the balance between efficiency and fairness.

Keywords: major power outrage emergency, electricity rationing, inoperability input-output model, fairness perception.

1 Introduction

Major power outrage emergencies (MPOEs) are defined as long-term unexpected large-scale power outage events in this paper, such as the Texas MPOE in USA in 2021 [15], Sichuan MPOE in China in 2022 [21], etc. MPOEs have caused significant economic, social, and health damages worldwide [9, 32]. Factors such as extreme weather [15], power structure [4], energy crisis [22], human factors [54] all contribute to the occurrence of the MPOE, making it inevitable, increasingly frequent and destructive [1, 25]. Therefore, it is pressing to effectively deal with the MPOE.

Researchers have reaped fruitful achievements in addressing the MPOE from technical and managerial perspectives. From the technical perspective, the researchers devote to developing energy storage system [2], uninterruptible power supply [30, 53], engine generator set [36], multi-energy system [28], etc. From the managerial perspective, scholars focus on MPOE risk prevention and control [10, 52], fault identification [29], fault repair [10], differentiated MPOE management strategies [18, 19].

Based on the review of the existing literature, four enlightenments are provided:

Firstly, in the long run, it is principal to cope with MPOEs through technological innovations [16]. However, countries are encountering technical barriers, shortage of funds, etc. [27]. Therefore, in the short to medium term, it is important to enhance the ability to deal with MPOEs through management methods based on the existing power supply systems and infrastructures.

Secondly, the current research primarily focuses on MPOE prevention and electricity restoration after MPOEs, but lacks attention to the limited electricity rationing during a MPOE. Given the long duration of MPOEs [32], the irrational electricity rationing decision-making is a major contributor to economic loss and social instability. Therefore, it is meaningful to optimize this process.

Thirdly, the affected regions have differentiated economic structures and populations, leading to differences in the quantity and urgency of electricity demands, as well as the magnitude of losses incurred [7, 49]. Therefore, it is practical to consider these differences when making electricity rationing decisions under MPOEs.

Fourthly, the existing papers mainly view MPOEs from the engineering perspective but lost sight of the social perspective [15]. The social dimension of MPOE management is reflected by the stakeholders' fairness perception to the electricity rationing [51]. In fact, people also have strong demands for the fair allocation of public resources and emergency resources [13, 14, 17, 27]. The electricity under MPOEs has the above two attributes, so its rationing fairness description is more challenging, but it has not received adequate attention. Therefore, it is valuable to establish a fair rationing decision-making model for electricity under MPOEs.

Based on the actual problems and research gaps aforementioned, this paper focuses on researching and solving the following three issues:

(1) How to quantify the efficiency of electricity rationing under MPOEs by considering the differences among affected regions?

(2) How to quantify the fairness of electricity rationing under MPOEs by combining its two attributes of public and emergency?

(3) How to make electricity rationing decisions under MPOEs by considering both efficiency and fairness simultaneously?

As an important part of losses from MPOEs, business interruption cost (BIC) is the production losses of the electricity and the ripple effects on other economic sectors because of their interconnectedness and interdependencies [11], which is directly related to the electricity rationing. Therefore, this paper uses the BIC to depict the efficiency of the electricity rationing.

To consider the difference of the affected regions, this paper applies the inoperability input-output model (IIM) to quantify the BIC. The IIM is based on the philosophy that the impact of loss of production in an industry is not limited to the industry itself but affects other industries that are dependent on it [3, 35]. Scholars have already used the IIM to make post-outrage BIC estimation [3, 11]. However, there is a lack of literature that advances BIC evaluation methods during MPOEs to support the electricity rationing decision-making.

In this study, the economic differences of affected regions are reflected in the Leontief's technology coefficient matrix and the regions' domestic products of multiple economic sectors. Additionally, this paper also uses the IIM in front to estimate the BIC as an efficiency indictor to support electricity rationing decision-making.

The fairness degree of electricity rationing is expressed in the stakeholders' fairness perception [8, 34]. The affected regions are the direct stakeholders of the electricity rationing. They would take other affected regions as reference points to compare their rationed electricity [33]. When faced with a better rationing reference point, the affected region will yield unfairness perception. Besides, if their electricity demand is more urgent than the reference point, their unfairness perception will be strengthed. Conversely, if their electricity demand is less urgent than the reference point, their original unfairness perception will be weakened. The situation is opposite when the reference point receives a worse rationing.

Since the affected regions' comparisons are bounded rational under emergency, this paper combines the value function of the Prospect theory to quantify their fairness perception [45, 46, 48]. The fairness gaps of electricity rationing are described from the perspective of each affected region based on their electricity demand and rationed electricity, which are used as the variable of the value function. The risk attitudes of affected regions are generated by the urgency of electricity demand which is described by the economic loss caused by the unit power shortage. By collecting the fairness perception of all affected regions, the fairness of electricity rationing can be determined.

This paper establishes an efficient fair electric rationing decision-making model to simultaneously consider the both dimensions. As the two objectives have different meanings and are crucial to electricity rationing, this paper uses the Pareto optimization idea to balance them. Besides, the electricity rationing requires to ration limited electricity to multiple affected regions while satisfying certain constraints, which is a complicated combinatorial optimization problem and presents NP-hard [41]. It is necessary to seek a proper heuristic algorithm to solve such a NP-hard problem. NSGA-II owns the dual characteristics of heuristic algorithm and the Pareto optimal idea, which is well adapted to the features of the problem [12]. Therefore, this paper combines NSGA-II to solve the proposed model.

Finally, taking Sichuan MPOE in 2022 as a numerical experiment to make simulation, this paper indicates the significant impact of "supercities" on the electricity rationing decision-making. Based on the discussions, this paper points out that the balance between efficiency and fairness should be valued, avoiding to pursue the extreme value of one side at the sacrificing excessively the other side.

The main contributions of this paper are listed as follows:

(1) This paper focuses on the electricity rationing problem under MPOEs, which has received insufficient concerned before and establishes an efficient fair electricity rationing decision-making model under MPOEs.

(2) The BIC is quantified in front to measure the efficiency of the electricity rationing. The economic differences of the affected regions are considered in the BIC quantification based on the IIM.

(3) This paper uses the fairness perception of the affected regions to quantify fairness of electricity rationing under MPOEs, and provides corresponding fairness perception quantification method.

(4) Sichuan MPOE in 2022 is designed as a numerical experiment to validate the proposed model, demonstrating the impact of "supercities" on the electricity rationing and the importance of the balance of efficiency and fairness.

The remainder of this paper is constructed as follows: Section 2 introduces some related concepts. Section 3 presents the derivation and construction of the proposed model. Section 4 provides a numerical experiment and carries out some relevant analyses. Some conclusions are summarized in Section 5.

2 Preliminaries

As the basis of this paper, some related concepts are presented including the definitions, causes and damages of MPOEs, as well as the fairness concern behavior of the affected regions.

2.1 Concept and definition

Based on the causes, power outages can be divided into expected outages (equipment maintenance, customer arrears, etc.) and unexpected outages (vandalism, equipment failure, extreme weather, etc.), with unexpected outages causing greater losses [25]. Depending on the time taken to restore power supply, long-term power needs several days or even weeks [32]. According to the scale of power supply reduction, large-scale power outage events are defined as the supply reduction of more than 5% in provincial administrative regions, 10% in large cities and 20% in middle and small cities [43]. Based on the above descriptions, this paper defines MPOEs as long-term unexpected large-scale power outage events.

2.2 Causes and damages of the MPOE

In modern society, almost all industries and daily life rely heavily on electricity, power outages are therefore one of the most significant threats to economic development, social stability, and health and safety [9, 15]. Severe power outrages may result in devastating outcomes. For example, 2021 Texas MPOE resulted in hundreds of deaths due to carbon monoxide poisoning, extreme cold, etc. [15].

A wide range of risks and uncertainties lead to MPOEs, including:

(1) **Extreme weather**. The frequency and severity of extreme weather are increasing, which has led to MPOEs worldwide [38], such as Puerto Rico MPOE caused by hurricane in USA in 2017 [5], Texas MPOE caused by winter storm in USA in 2021 [15], and Sichuan MPOE caused by high-temperature drought weather in China in 2022 [21].

(2) **Power structure**.Since the adoption of the Paris Agreement, many regions have substantially increased their renewable energy generation, especially wind and solar energy[53]. However, it is challenging to integrate renewable into power systems due to their variability and limits in controllability and predictability [4]. Compounded by uncertainties in power demand and inefficient storage capacities, it is arduous to maintain a delicate balance between electricity supply and demand [49]. Besides, some regions depend heavily on a single electricity production, increasing the risks of MPOEs.

(3) **Energy crisis**.The precipitous decline in Europe-Russia energy trade has worsened the ongoing global energy crisis. The soaring prices of gas and coal have exerted huge upward pressure on electricity costs worldwide. Many regions are compelled to cut down on electricity production and face with unprecedented MPOE shocks [22].

(4) **Human factor**.Intentional cyber-physical attract is the second leading cause of MPOEs in the USA [9]. Russian strikes at Ukraine have left much of Ukraine's energy system lying in ruins [54]. Moreover, huge terrorist attacks globally also lead to MPOEs [32].

Based on the above exposition, MPOEs are inevitable, with increasing frequency and destruction [1]. Therefore, it is imperative to study deeply how to deal with MPOEs.

2.3 Fairness concern behavior

Since the electricity under MPOEs has two attributes of public and emergency, the affected regions are the direct stakeholders of the electricity rationing and require to be treated fairly. If they feel unfair, they may take punitive measures to regain a sense of psychological fair, such as protesting or even deliberately sabotaging the electricity rationing [31]. It is essential for maintaining social stability and reducing the loss caused by secondary disasters to consider stakeholders' fairness concern behaviors.

The limited electricity needs to be rationed to multiple affected regions under MPOEs. Allocating more electricity to a certain region implies a reduction in available electricity for other affected regions. Furthermore, the public resources are owned by the masses. The equity theory [6, 33] suggests that the affected regions will make mutual comparisons in electricity rationed with other regions to judge whether being treated fairly [42].

Since the loss of each affected region is directly related to the rationed electricity, each affected region is more concerned about its own situation rather than the overall loss of all affected regions, and the mutual comparisons under emergency are bounded rational [24, 45, 46]. When facing other affected regions receiving more electricity than them, they would produce "unfairness" perception [47]. Additionally, the electricity demand urgency of the affected regions also affects their fairness perception. For example, when faced with an affected region receiving more electricity, the "unfairness" perception is slight if the electricity need of the affected region is more urgent, but strong if the electricity need is not as pressing as theirs [39].

Based on the above elaboration, this paper attempts to depict the affected regions' fairness perception through their bounded rational comparisons and power need urgency differences. Figure 1 illustrates the relationship among fairness concern behaviors of the affected regions, electricity under MPOEs and the related theories.

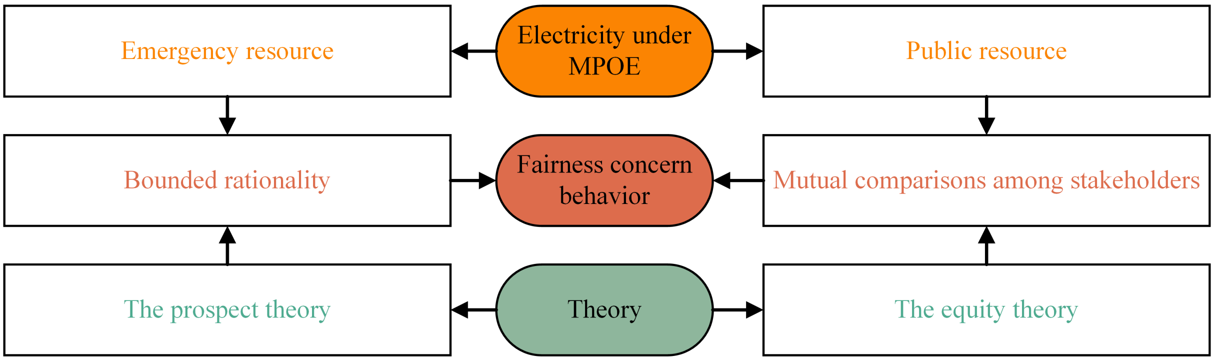

Figure 1: The relationship among fairness concern behavior, electricity under MPOE and related theories

3 Efficient fair electric rationing decision-making model under MPOEs

This section offers a decision-making model for the rationing of electricity during a MPOE, encompassing the derivation and construction processes of the proposed model.

3.1 Problem description

To describe problem clearly, this paper divides electricity into basic electricity (household electricity consumptions, important equipment maintenance, etc.) and business electricity (electricity for economic activities). The basic electricity is prioritized over the business electricity in electricity rationing decision-making. According to the degree of the MPOE, this paper divides the decision scenarios of electricity rationing into two categories:

Decision scenario 1: The disposable electricity is insufficient to meet the basic electricity consumptions. At this time, the power shortage is quite serious, it should take multi-resource electricity generation, remote electricity support, etc. to expand the disposable electricity [28]. In this scenario, all disposable electricity is rationed to basic electricity consumptions. This decision scenario is relatively simple and not discussed in this paper.

Decision scenario 2: The disposable electricity meets the basic electricity consumptions of affected regions, but insufficient to meet their business electricity consumptions. After guaranteeing basic electricity consumptions, the remaining electricity will be rationed to multiple affected regions for economic activities. In this rationing, it is necessary to consider not only the quantity and urgency of electricity demand, and the economic differences of the affected regions, but also the fairness appeals of multiple affected regions. The electricity rationing in this decision scenario is more complicated and is the focus of this paper.

This paper attempts to support the electricity rationing decision-making from the two dimensions of efficiency and fairness. Firstly, the efficiency of electricity rationing is described through the affected regions' BICs caused by MPOEs. Secondly, the fairness of electricity rationing is quantified through the affected regions' fairness perception for the rationing. The notations used in this paper are summarized in Appendix A.

3.2 Efficiency description

This subsection shows the process of efficiency quantification. Subsection 3.2.1 provides a BIC estimation method based on the IIM. Subsection 3.2.2 presents the description of affected regions' economic characteristics. Subsection 3.2.3 gives an inoperability quantification method.

3.2.1 BIC estimation based on the IIM

The IIM portrays the relationship between inoperability and BICs of the affected regions as Eq. (1), and its derivation process is shown in Appendix B [3].

$$[L_i] = [diag(\widehat{x}_i)] \times [I - A_i^*] \times [q_i] \tag{1}$$

where $diag(\widehat{x}_i)$ and A_i^* can reflect the characteristics of economic structures of the affected region i. I is a m-dimensional unit matrix. $[q_i] = [q_i^1, q_i^2, ..., q_i^j, ..., q_i^m]^T$ is the inoperability vector in the region i caused by the MPOE, where q_i^j is the inoperability of the economic sector j in the region i. $[L_i] = [L_i^1, L_i^2, ..., L_i^j, ..., L_i^m]^T$ is the BIC vector of the region i, where L_i^j is the BIC of economic sector j in the region i.

The larger the BICs are, the lower of the efficiency is. Therefore, the efficiency E of the electricity rationing is quantified as the opposite of the sum of all the affected regions' BICs as:

$$E = -\sum_{i=1}^{n}\sum_{j=1}^{m} L_i^j \tag{2}$$

3.2.2 Economic characteristic description for multiple regions

In Eq. (1), $[diag(\widehat{x}_i)] \times [I - A_i^*]$ reflects the characteristic of economic structure of the region i. $[diag(\widehat{x}_i)]$ is a diagonal matrix, which is conducted as:

$$[diag(\widehat{x}_i)] = \begin{bmatrix} x_i^1 \\ x_i^2 \\ \vdots \\ \widehat{x}_i^j \\ \vdots \\ \widehat{x}_i^m \end{bmatrix} = \begin{bmatrix} x_i^1 & 0 & 0 & 0 & 0 & 0 \\ 0 & x_i^2 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \widehat{x}_i^j & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \widehat{x}_i^m \end{bmatrix} \tag{3}$$

where $\widehat{x}_i^j$ is expressed as the planned production of the economic sector j in the region i, which is described as the domestic product of the economic sector j in the region i.

$[A_i^*] = [diag(\widehat{x}_i)]^{-1} \times [A_i] \times [diag(\widehat{x}_i)]$ describes the relationships among economic sectors in the region i, where $[A_i]$ is the Leontief's technical coefficient matrix of m economic sectors, showing these sectors' interindustry relationships [35].

3.2.3 Inoperability quantification

The inoperability of IIM in this paper is defined as the inability of economic sectors to perform their intended functions due to MPOEs [26].$[q_i] = [q_i^1, q_i^2, ..., q_i^j, ..., q_i^m]^T$ is the inoperability vector of the region i, where q_i^j is the inoperability of the economic sector j in the region i and is quantified as the percentage reduction in electricity supply due to the MPOE in this paper [35]. The quantification method of q_i^j is defined as:

$$q_i^j = \frac{electricity\ gap\ of\ economic\ sector\ j\ in\ region\ i}{electricity\ demand\ of\ economic\ sector\ j\ in\ region\ i} \tag{4}$$

This paper considers the electric rationing among the affected regions and ignores the electric rationing among economic sectors in the same affected region. Therefore, this subsection assumes that the inoperability of all economic sectors in a region are the same. The q_i^j is quantified as:

$$q_i^j = \frac{EC_i - x_i}{EC_i} \tag{5}$$

where EC_i is the electricity demand of the affected region i, x_i is the electricity rationed to the affected region i.

3.3 Fairness description

This subsection presents the fairness quantification method of electricity rationing under MPOEs.

3.3.1 Reference point determination

According to Subsection 2.3, all affected regions are the direct stakeholders of electricity rationing and there are competitions among them. Therefore, the affected regions will take other affected regions as reference points to reap fairness perception. For example, there are 5 affected regions needed to be rationed electricity, $i = 1, 2, 3, 4, 5$. The affected region 1 would compare the received electricity with other 4 affected regions. Then the fairness perception of the affected region 1 can be described as $p_1 = p_{12} + p_{13} + p_{14} + p_{15}$.

3.3.2 Fairness gap calculation

This subsection adopts two comparative ways to obtain the fairness gaps among affected regions.

Relative fairness gap: The affected regions would compare the satisfaction degree of electricity demand with other affected regions to obtain fairness gaps.

Absolute fairness gap: Under emergency, the affected regions would also directly focus on the amount of electricity they received, and compare the amount with other affected regions.

Δg_{ir}^k is the fairness gap between the affected region i and the affected region r under $k-$th comparative way, which is calculated as:

$$\Delta g_{ir}^k = \begin{cases} \dfrac{x_i}{EC_i} - \dfrac{x_r}{EC_r} & k = 1 \\ \dfrac{x_i - x_r}{\max\{x_i, x_r\}} & k = 2 \end{cases} \tag{6}$$

where $k \in K$, $K = \{1, 2, ..., u\}$, u is the number of comparative ways. $k = 1$ indicates the relative fairness gap, and $k = 2$ is the absolute fairness gap. $\Delta g_{ir}^k > 0$ means the affected region i believes it has a better rationing than the affected region r under the $k-$th comparative way, and vice versa.

3.3.3 Risk attitude description

On the basis of ensuing the basic electricity needs of the affected regions, the remaining electricity is used for economic activities. Therefore, the risk attitudes of the affected regions will be influenced by their electricity demand urgencies. $ECPG_i$ is the economic loss per unit of electricity shortage in the region i as Eq. (7), which is the most intuitive and easily accessible for the affected regions.

$$ECPG_i = \frac{GDP_i}{EC_i} \tag{7}$$

The bigger $ECPG_i$ is, the more urgent electricity demand of the affected region i will be, Therefore, this subsection uses $ECPG_i$ to portray the risk attitude of the affected regions as follows:

$$\alpha_{ir} = \begin{cases} \dfrac{2ECPG_i - ECPG_r - \min ECPG}{2(ECPG_i - \min ECPG)} & ECPG_i \geq ECPG_r \\ \dfrac{\max ECPG - ECPG_r}{2(\max ECPG - ECPG_i)} & ECPG_i < ECPG_r \end{cases} \tag{8}$$

$$\alpha_{ir} = \begin{cases} \dfrac{ECPG_r - \min ECPG}{2(ECPG_i - \min ECPG)} & ECPG_i \geq ECPG_r \\ \dfrac{ECPG_r + \max ECPG - 2ECPG_i}{2(\max ECPG - ECPG_i)} & ECPG_i < ECPG_r \end{cases} \tag{9}$$

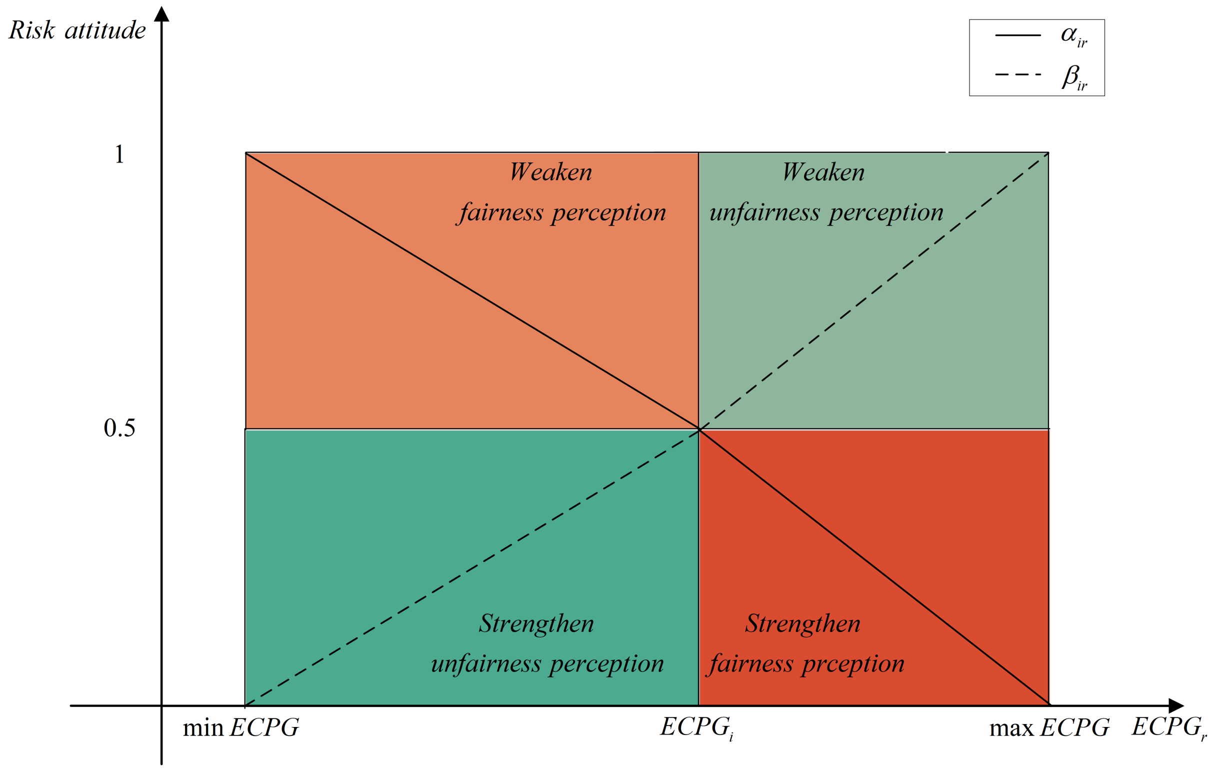

Figure 2: Description of risk attitude

When the affected region i takes the affected region r as the reference point, if $\Delta g_{ir}^k > 0$, then the affected region i will take a gain risk attitude α_{ir} to reap fairness perception. As the full line in Figure 2 shows, $ECPG_i > ECPG_r$ means that the affected region i has higher urgent electricity demands than the affected region r, which will take the affected region i a sense of "expected gain" and thus weaken the fairness perception of the affected region i. On the contrary, $ECPG_i < ECPG_r$ will take the affected region i a sense of "unexpected gain" and thus strengthen the fairness perception of the affected region i.

On the opposite, $\Delta g_{ir}^k < 0$ means that the affected region i takes a loss risk attitude β_{ir} to reap unfairness perception. As the broken line in Figure 2 shows, $ECPG_i > ECPG_r$ will take the affected region i a sense of "unexpected loss" and strengthen the unfairness perception of the affected region i. $ECPG_i < ECPG_r$ will take the affected region i a sense of "expected loss" and weaken the original unfairness perception.

3.3.4 Fairness perception quantification

This paper combines the value function of the Prospect theory to quantify the fairness perception of affected regions. The fairness gaps are taken as the inputs of the value function as Eq. (10) and Figure 3:

$$p_{ir}^k = \begin{cases} (\Delta g_{ir}^k)^{\alpha_{ir}} & \Delta g_{ir}^k > 0 \\ 0 & \Delta g_{ir}^k = 0 \\ -\lambda(-\Delta g_{ir}^k)^{\beta_{ir}} & \Delta g_{ir}^k < 0 \end{cases} \tag{10}$$

where p_{ir}^k is the fairness perception of the region i while taking the region r as the reference point under the $k-$th comparison way. λ is the loss aversion coefficient of the affected regions. Based on the research of Tversky and Kahneman [45], this paper sets $\lambda = 2.25$.

In Figure 3, the red, yellow and green curves are the fairness perception functions for the affected region i facing the affected region r with higher, the same and lower urgent electricity demands, respectively. When $\Delta g_{ir}^k > 0$, the function is in the first quadrant and the affected region i will obtain positive fairness perception. In this quadrant, if the electricity demand urgency of the affected region r is higher, it will strengthen the fairness perception as red curve, otherwise, the fairness perception will be weakened as green curve. When $\Delta g_{ir}^k < 0$, the function is in the third quadrant and the affected region i will reap unfairness perception. In the third quadrant, higher electricity demand urgency of the affected region r will weaken the unfairness perception as red curve, and lower electricity demand urgency of the affected region r will strengthen the unfairness perception as green curve.

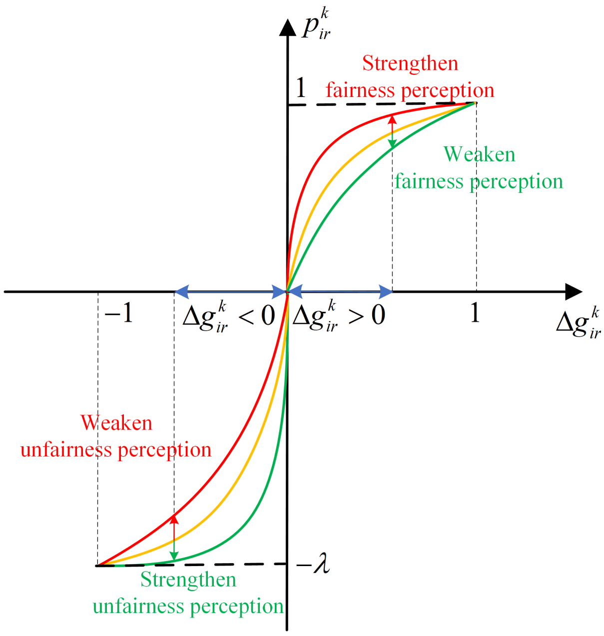

Figure 3: Fairness perception quantification

Collecting all the affected regions' fairness perception, the fairness of electricity rationing is gained as:

$$F = \sum_{i=1}^{n} \sum_{r=1, r\neq i}^{n} \sum_{k=1}^{u} p_{ir}^k \tag{11}$$

3.4 Model formulation and solution strategy

Based on the above elaboration, the efficient fair electricity rationing decision-making model is described as follows:

$$\max E \tag{12}$$

$$\max F \tag{13}$$

Subject to

$$DNE_i \leq x_i \leq EC_i \tag{14}$$

$$\sum_{i=1}^{n} x_i = DE \tag{15}$$

Herein, Eqs. (12)-(13) are the objective functions of maximizing the efficiency and maximizing the fairness respectively. Eq. (14) delineates that the electricity rationed to each affected region satisfies their basic electricity consumptions but not more than their electricity demands. Eq. (15) means that all disposable electricity will be rationed.

Most of the combinatorial optimization problems are NP-hard and it is necessary to seek a proper heuristic algorithm to solve such a NP-hard problem [37, 41]. Besides, multiple objectives are difficult to achieve optimum at the same time, while Pareto optimal idea has been proven an effective method to balance multiple objectives well [50, 51]. NSGA-II owns the dual characteristics of heuristic algorithm and Pareto optimal idea [12], so it is well adapted to the features of the proposed model. Therefore, this paper attempts to combine NSGA-II to solve the proposed model.

4 Case study

This section reviews the Sichuan MPOE in 2022 firstly, and then takes it as an example to conduct a numerical experiment to validate the proposed model. Some management suggestions are provided based on the corresponding analyses.

4.1 Sichuan MPOE in 2022

Hydropower is the biggest source of electricity supply in Sichuan. By the end of 2021, the hydropower capacity stood at 89.47 million KW. The total power generation of Sichuan was about 417.3 billion KWH, with nearly 80% of them coming from hydropower. Sichuan's annual maximum electricity load was 51.91 million KW in 2021. Not only is there no electricity shortage in Sichuan theoretically, but the surplus electricity can be sent to eastern coastal regions such as Shanghai, Jiangsu, Zhejiang, etc. [21].

However, in July and August 2022, Sichuan suffered from a wide range of long-term extreme high temperature and drought weather, facing the situation of "three most" superimposition, that is, the highest temperature, the least rainfall and the highest electricity load. Firstly, Sichuan experienced its fiercest heat wave in 60 years, with temperatures crossing 40 degrees Celsius in dozens of cities. Secondly, rainfall of Sichuan fell 30% in July and 60% in August compared to the seasonal averages. The waterlines of hydropower stations were at the lowest level in the same period of history, severely curtailing hydropower generation capacity. Thirdly, the electricity load hit the record, reaching 65 million KW, where the air-conditioning load had increased significantly. Taking Chengdu, Sichuan as an example, the air-conditioning load had accounted for 40-50% of the city's electricity load in the peak period [44].

A significant reduction in hydropower and a severe increase in power load resulted in a large electricity supply and demand gaps, which triggered a MPOE. To deal with the MPOE, the authorities of Sichuan ordered all industrial electricity users to shut down for 11 days (from 00:00 on August 15th to 24:00 on the 25th). Figure 4 overviews the situation of Sichuan MPOE in 2022.

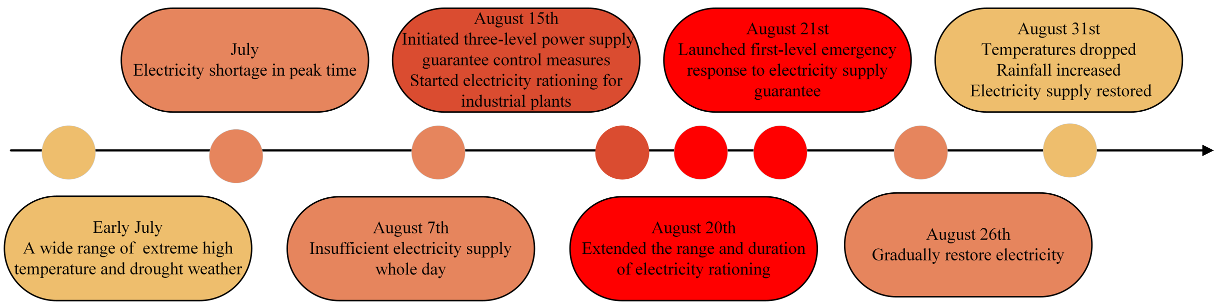

Figure 4: Overview of Sichuan MPOE in 2022

4.2 Parameter setting

This subsection takes 15 cities of the Sichuan province as the affected regions to carry out a numerical experiment. The time period for electricity rationing is 11 days. The disposable electricity is set as the 80% of the total electricity demand of all affected regions. The electricity demands of all affected region are set as their annual electricity consumptions. Since the basic electricity consumptions are difficult to collect, this paper regards the household electricity consumptions as the basic electricity consumptions. Table C.1 in Appendix C shows the annual electricity consumptions, business electricity consumptions, household electricity consumptions of all affected regions.

The National Bureau of Statistics of China provides a competitive input-output table of 153 economic broad groupings in 2020 [40]. However, it is difficult to collect the domestic product of all the above economic broad groupings of each region. To facilitate data collection, 134 broad groupings are selected and then summarized into 8 economic sections in terms of the industrial classification for national economic activities of China.

Since the data in the latest competitive input-output table are calculated at producers' prices in 2020, the domestic products of 8 economic sections also use the data from the year 2020 which is shown in the Table C.2. of Appendix C. The Leontief's technical coefficient matrix of the 8 economic sections is calculated and displayed in Table C.3 of Appendix C.

4.3 Results and discussion

30 Pareto frontiers are generated and shown in Figure 5, where the abscissa is the efficiency dimension, i.e., the sum of BICs of all affected regions ($10^4 CNY$), and the ordinate is the fairness dimension, i.e., the sum of fairness perception of all affected regions.

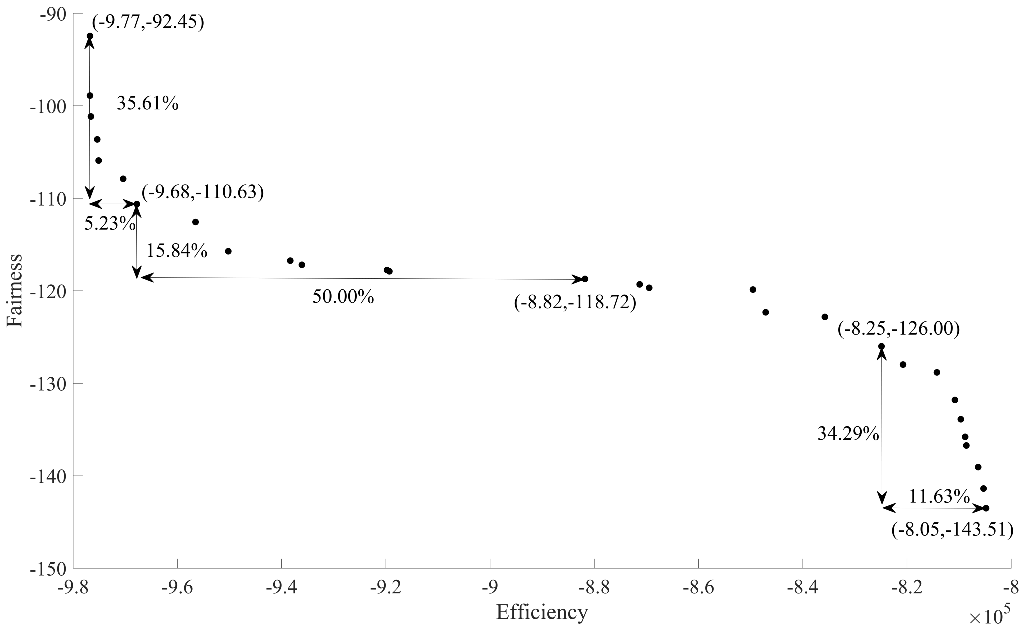

Figure 5: The Pareto frontiers

It can be seen in Figure 5, when the fairness is low, sacrificing a small part of efficiency (nearly 11.63%) can be exchanged for a large part of fairness improvement (nearly 34.29%). As the fairness increases, even though a large part of efficiency is sacrificed (nearly 50%), only a small part of fairness (nearly 15.84%) can be improved.

However, what is interesting is that when the fairness is already at a high level, sacrificing a small part of efficiency (nearly 5.23%) can still significantly increase the fairness (nearly 35.61%), which is different from the previous Pareto frontier analyses. This subsection attempts to explain this phenomenon.

Chengdu is the capital and the biggest city of Sichuan province, with GDP and electricity consumptions accounting for nearly 36.45% and 24.09% of Sichuan respectively. Therefore, the electricity rationed to Chengdu directly affects the efficiency of the whole electricity rationing. It will inevitably lead to reductions in the available electricity for other affected regions if Chengdu takes up too much electricity, which affects the fairness of the whole electricity rationing. The relationship between the electricity rationed to Chengdu and the objectives of efficiency and fairness is shown in Figure 6.

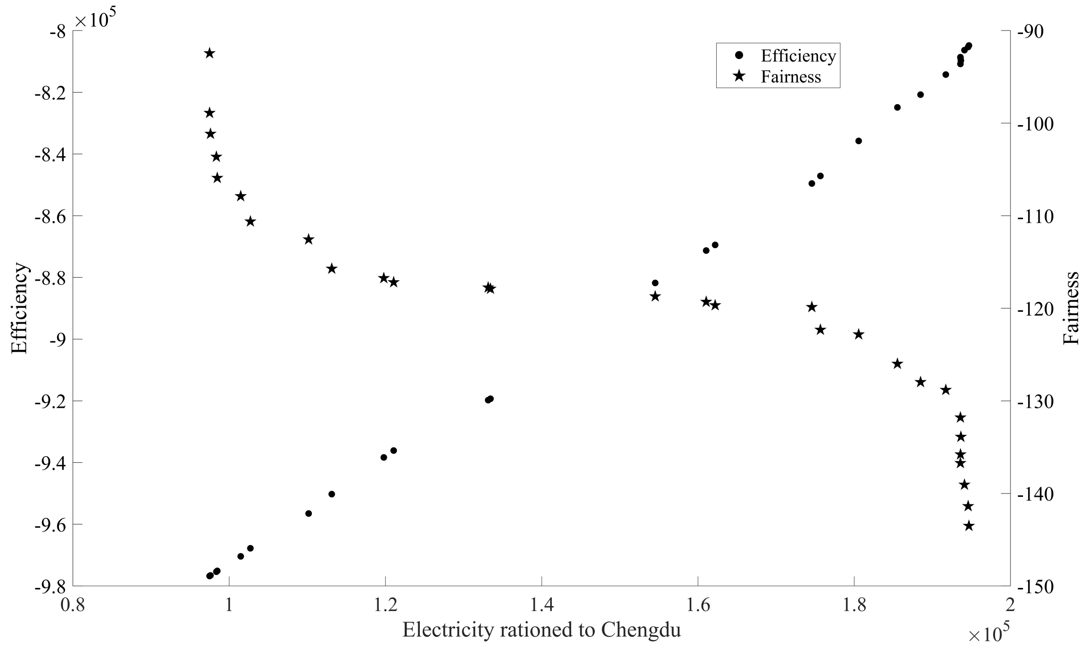

Figure 6: The relationship of electricity rationed to Chengdu and the objectives of efficiency and fairness

The Pearson correlation coefficients between electricity rationed to Chengdu and the efficiency and fairness of electricity rationing are 0.9993 and -0.9182 respectively. That is to say, the more electricity is rationed to Chengdu, the higher efficiency is, and at the same time, the lower the fairness will be.

To enhance the fairness, it is inevitable to continuously reduce the electricity rationed to Chengdu. At this time, although being rationed more electricity than other affected regions, the satisfaction degree of electricity demand in Chengdu will be lower than other affected regions due to its high electricity demand.

Under this circumstance, the $\Delta g_{ir}^{k}(k = 2)$ (relative fairness gap) of other affected regions will be positive, which brings them a sense of "unexpected gain". This explains the scenario in Figure 5, i.e., when fairness is already high, sacrificing a small part of efficiency can still significantly increase the fairness. Although the sacrificed efficiency is small at this time, more efficiency needs to be sacrificed in advance to achieve this state.

After removing Chengdu, the Pareto frontiers are shown in Figure 7 which is similar to Figure 6, where sacrificing a small part of one objective can significantly improve the other objectives when the objective is already superior. However, the "special" phenomenon in Figure 6 does not exist in Figure 7. Therefore, the existence of the "supercities" can obviously affect the electricity rationing under MPOEs, especially in the fairness dimension. Based on the above statements, two management suggestions can be obtained:

Firstly, in the process of electricity rationing decision-making, it is significant to strike a balance between fairness and efficiency, avoiding overly pursuing the excellence of one objective at much expense of the other objectives.

Secondly, for regions with "supercities", attention needs to be paid to maintain the balance between "supercities" and other cities. When the degree of fairness is low, sacrificing a small portion of electricity rationed to the "supercities" can increase the fairness distinctly. However, it is inevitable to sacrifice excessive benefits of the supercities to achieve an extremely high fairness, which results in great efficiency losses of the whole electricity rationing. It should also be avoided.

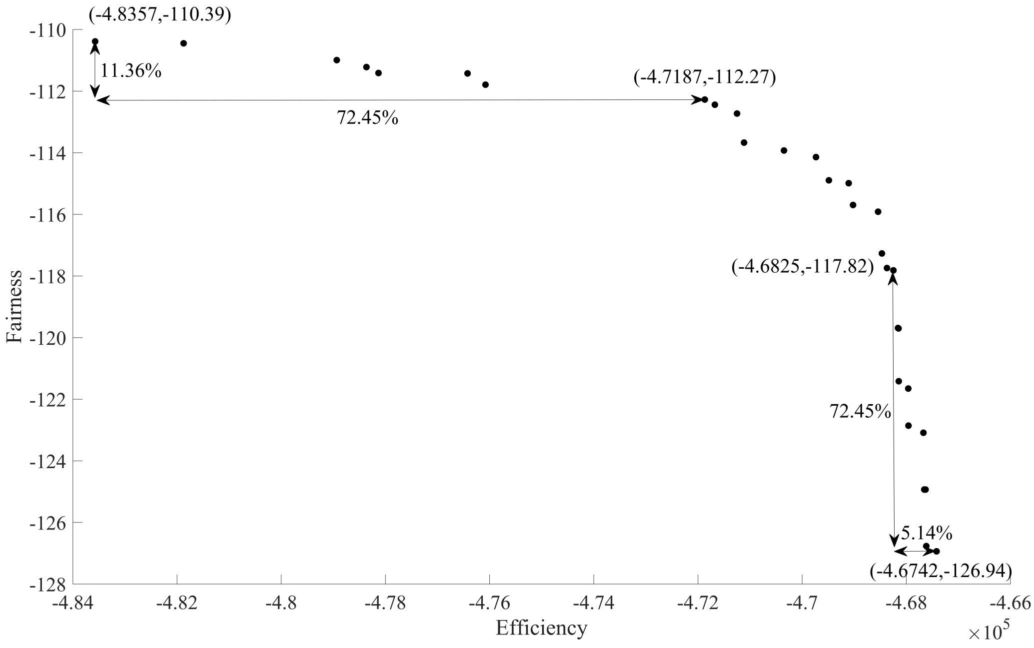

Figure 7: The Pareto frontiers without Chengdu

4.4 Conclusions

This paper focuses on the electricity rationing problem under MPOEs, which has received insufficient attention in previous literature. To optimize the problem, this paper proposes an efficient fair electricity rationing decision-making model and two quantification methods for the efficiency and the fairness respectively. Sichuan MPOE in 2022 is designed as a numerical example to verify the proposed model and some management suggestions are provided correspondingly. It is obvious that the deployment of the method proposed implies a collaborative decision-making process carried out by several stakeholders [20, 23].

However, there still exist some deficiencies of this paper. In the BIC quantification, this paper only considers the relationships among economic sectors within the same region, but does not consider the relationships among economic sectors of different regions, such as their upstream-downstream relationships. Secondly, this paper assumes that the inoperability of all economic sectors in an affected region is the same, disregarding the potential differences in electricity rationing of these sectors.

For some developing areas with long-term, frequent and predictable power outrages, how to ration electricity in these areas is an interesting topic in the future. Besides, the risk attitudes of the affected regions in this paper only considers the economic factor. It is meaningful to consider politics, humanities, etc. in risk attitudes description in the decision-making for public or emergency resources rationing further.

Conflict of interest

The authors declare no conflict of interest.

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Appendix

A Notation description

Table A.1: Description of notations

Notation	Description
Sets and indexes	
i, r	The $i-$th and $r-$th affected region, $i, r \in I$, $I = \{1, 2, ..., n\}$, n is the number of affected regions
j	The $j-$th economic sector, $j \in J$, $J = \{1, 2, ..., m\}$, m is the number of economic sectors
k	The $k-$th comparison way, $k \in K$, $K = \{1, 2, ..., u\}$, u is the number of comparison ways
Parameter	
EC_i	Electricity demand of affected region i
DEN_i	Domestic electricity need of affected region i
DE	Disposable electricity
$ECPG_i$	Economic loss per unit of electricity shortage in affected region i
GDP_i	Gross domestic product of affected region i
$\widehat{x}_i^j$	The planned production of economic sector j in affected region i
Function	
q_i^j	The inoperability of economic sector j in affected region i
L_i^j	The BIC of economic sector j in affected region i
p_{ir}^k	The fairness perception of affected region i while taking affected region r as the reference point under $k-$th comparison way
Variables	
x_i	The quantity of electricity rationed to affected region i
Objective	
E	The efficiency of the electricity rationing
F	The fairness of the electricity rationing

B Inoperability input-output model

The original Leontief input-output model is as:

$$x = A \times x + c \tag{B.16}$$

where $x = [x_1, x_2, ..., x_m]$ presents the total production of different economic sectors, $c = [c_1, c_2, ..., c_m]$ indicates the end user demand, $[A]$ shows the technology coefficient matrix among economic sectors.

Then, combing the Leontief formulation, the balance between the reduction in production and the reduction in final demand can be gotten as follows:

$$\widehat{x} - \widetilde{x} = A \times [\widehat{x} - \widetilde{x}] + [\widehat{c} - \widetilde{c}] \tag{B.17}$$

where $\widehat{x}$ and $\widetilde{x}$ are the planned production and the reduced production respectively. $\widehat{c}$ and $\widetilde{c}$ are the planned demand and reduced demand respectively.

To describe the unit reduction in production, inoperability input-output model is derived as follows:

$$[q] = [A^*] \times [q] + [diag(\widehat{x})]^{-1} \times [\widehat{c} - \widetilde{c}] \tag{B.18}$$

where $[q]$ is the inoperability vector and can be defined as $[q] = [diag(\widehat{x})]^{-1} \times [\widehat{x} - \widetilde{x}]$. $[A^*]$ can captures the interindustry relationship and $[A^*] = [diag(\widehat{x})]^{-1} \times [A] \times [diag(\widehat{x})]$.

Then, the BIC can be estimated as follows:

$$L = [\widehat{c} - \widetilde{c}] = [diag(\widehat{x})] \times [I - A^*] \times [q] \tag{B.19}$$

where L is the estimated BIC. $[diag(\widehat{x})] \times [I - A^*]$ can reflects the characteristics of economic structure and interindustry relationships. I is a unit matrix. And $[q]$ is the variable.

C Data

Table C.1: Electricity consumptions of affected regions

i	**Affected regions**	**Annual electricity consumption**($10^4 kwh$)	**Business electricity consumption**($10^4 kwh$)	**Household electricity consumption**($10^4 kwh$)
1	Chengdu	6938431	5874853	1063578
2	Zigong	426902	323724	103178
3	Panzhihua	1352811	1301458	51353
3	Panzhihua	1352811	1301458	51353
4	Luzhou	963831	861846	101985
5	Deyang	1285725	1150100	135625
6	Mianyang	1154644	1001675	152969
7	Guangyuan	598569	531293	67276
8	Suining	506884	430546	76338
9	Neijiang	806652	728215	78437
10	Nanchong	789909	662610	127299
11	Yibin	1019631	904523	115108
12	Dazhou	916092	860765	55327
13	Yaan	1125100	1081411	43689
14	Bazhong	351582	297773	53809
15	Ziyang	279156	234018	45138

The data were collected from the China City Statistical Yearbook.

Table C.2: Gross domestic product and its composition by economic sections

Region	Primary Industry ($10^4 CNY$)	Secondary Industry ($10^4 CNY$)		Tertiary Industry ($10^4 CNY$)					Gross domestic product ($10^4 CNY$)
	Agriculture, Forestry, Animal Husbandry and Fishery	Industry	Construction	Wholesale and Retail trades	Transport, Storage and Post	Hotels and Catering services	Financial intermediation	Real estate	
Chengdu	6551691	42082746	13122706	16814488	8970877	4580973	21148092	14877813	177166756
Zigong	2343722	4064862	1618200	1242949	234753	311937	595729	1203955	14584392
Panzhihua	977143	4790574	802780	742705	412460	210217	217970	322404	10408243
Luzhou	2613077	7030610	3354536	1959014	254650	327184	917548	1488081	21572178
Deyang	2854276	10200763	1093465	2465167	556538	623533	925154	908839	24041250
Mianyang	3839943	8826540	2927106	2484620	516289	672550	1250409	1843570	30100767
Guangyuan	1916140	2925969	1005281	666032	246048	187280	342719	543948	10080092
Suining	2248794	5032050	1322105	765572	137941	178478	611324	1005347	14031793
Neijiang	2749282	3635695	1157933	1575138	519922	354379	550238	845309	14658841
Nanchong	4672529	5886997	3222500	356405	1490208	463338	1106938	1732594	24010754
Yibin	3511081	10128407	3372697	2050310	433449	245042	913379	2152775	28021249
Dazhou	4046241	4799235	2620185	2565724	305680	418990	816081	1486379	21178017
Yaan	1539900	2021100	248200	638400	114500	178100	357400	596000	7545900
Bazhong	1655596	1216524	934179	504372	97309	212468	350437	580151	7669866
Ziyang	1817331	1612980	675200	696641	38482	228736	421564	566438	8075024

The data were collected from the Statistical Yearbook of regions.

Table C.3: Leontief's technical coefficient matrix

	Agriculture, Forestry, Animal Husbandry and Fishery	Industry	Construction	Wholesale and Retail trades	Transport, Storage and Post	Hotels and Catering services	Financial intermediation	Real estate
Agriculture, Forestry, Animal Husbandry and Fishery	0.8737	-0.0504	-0.0067	0.0000	-0.0001	-0.1126	-0.0001	-0.0003
Industry	-0.1855	0.4311	-0.4799	-0.0385	-0.2230	-0.3446	-0.0477	-0.0237
Construction	-0.0007	-0.0005	0.9640	-0.0010	-0.0014	-0.0024	-0.0035	-0.0126
Wholesale and Retail trades	-0.0226	-0.0465	-0.0489	0.9931	-0.0240	-0.0585	-0.0063	-0.0028
Transport, Storage and Post	-0.0219	-0.0302	-0.0299	-0.0645	0.8842	-0.0338	-0.0166	-0.0045
Hotels and Catering services	-0.0023	-0.0047	-0.0063	-0.0055	-0.0156	0.9974	-0.0364	-0.0042
Financial intermediation	-0.0130	-0.0174	-0.0365	-0.0444	-0.0928	-0.0107	0.9171	-0.1118
Real estate	0.0000	-0.0003	-0.0001	-0.0618	-0.0087	-0.0410	-0.0837	0.9666

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