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Heat wave, electricity rationing, and trade-offs between environmental gains and economic losses: The example of Shanghai

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HIGHLIGHTS

- Many megacities suffer from more frequent heat wave events in recent decades.
- We propose a tool for the management of electricity shortage caused by heat wave shocks.
- The tool aims to eliminate the shock incidents of blackouts and brownout.
- It minimizes economic cost and maximize environmental gain of management measures.

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ABSTRACT

In recent decades, many megacities in the world have suffered from increasingly frequent heat waves. During heat waves, air-conditioners, refrigerators, and electric fans add a considerable peak demand on electrical utility grids, and on the supply side, high temperatures exert adverse effects on electricity generation, transmission, and distribution. Without pro-active planning and mitigation measures, the overloading would result in more frequent blackouts (the complete failure of electricity distribution) and brownouts (voltage reductions). To facilitate a pro-active planning, which aims to replace blackouts and brownouts by a rationing regime in selected sectors, this research proposes an integrated modeling tool which couples a regression model between daily electricity use and maximum temperature over the summer and a mixed input–output model with supply constraints. With the help of available data in Shanghai, China, we show that this tool is capable of quantitatively estimating the overall economic effects and sequential changes in carbon emissions, which a given magnitude of power rationing in a specific sector can exert across all sectors. The availability of such information would enable decision makers to plan an electricity rationing regime at the sector level to meet the double criterions of minimizing the overall economic losses and maximizing the extent of carbon emission reduction.

1. Introduction

In the Summary for Policymakers of the Working Group III to the 5th Assessment Report of the IPCC, it is clearly stated that in the last 130 years, the world has warmed by approximately 0.85 °C; and furthermore, each of the last 3 decades has been successively warmer than any preceding decade since 1850 [1]. This increasing global warming trend, in combination with the heat-island effects of large urban establishments, has led to more frequent events of heat waves in many mega-cities across the world in recent decades. Extreme high air temperatures lasting for several days can contribute directly to deaths from cardiovascular and respiratory disease, particularly among elderly people. For example, in the heat wave of summer 2003 in Europe, more than 70,000 excess deaths were recorded [2]. To mitigate the adversary impact of a heat wave on human health and to save human lives, power suppliers should grant the top priority to the

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cooling of residential and working spaces in power supply management. However, when air-conditioners, refrigerators, and electric fans add heavier power loads to the grid, blackouts (the complete failure of electricity distribution) and brownouts (voltage reductions) may occur as the power companies struggle to deal with the heat wave-caused problems with generation, transmission and distribution, in addition to the burden of overloading [3,4].[1] This tension is much higher in big cities where economy is booming and demand for electricity increases rapidly owing to fast social-economic development and population growth. For example, the air conditioner ownership in Shanghai has increased from 93 in 2003 to 207 in 2013 per hundred households [7]. During heat wave, electricity shortage in Shanghai often reaches 1 million kW h or even a much higher level, and consequently, power rationing has to be imposed on certain sectors with very short notice [8].

Much research attention has been paid to the design of a power rationing regime. Given the complexity in assessing the direct and indirect impact of power rationing across many social and economic systems, decision-making regimes based on expert opinions has been regarded as the most practical approach [9–13]. However, experts' opinions are often diverse and difficult to be quantified and standardized. As a consequence, it is hard to monitor and objectively evaluate such decision-making processes. In the case where biased opinion driven by conflict interests become influential, the resultant rationing plan could lead to more social and economic problems than the plan could solve. Fahrioglu and Alvarado [14] employed the 'revelation principle' of game theory to design incentive compatible contracts for encouraging customers to participate in a demand management program. The goal of this approach is to get certain load relief when needed and to do so in a cost effective way. While such a theoretical design is potentially helpful to reduce the peak load during a heat wave, it is unclear where the boundary should be for the cost-benefit calculation by the contracting parts in practice. In other words, it would be very difficult for such a contract to incorporate indirect impacts on upstream and downstream sectors.

In this research, we propose an integrated modeling tool that combines a regression model, which quantifies the relationship between daily electricity use (or peak load) and daily maximum temperature, and a mixed input–output model with supply constraints. This tool is designed to facilitate a pro-active rationing regime in selected sectors with the intention to avoid shocks of sudden blackouts and brownouts. The close relationship between daily maximum temperature and daily electricity consumption or peak load in summer months has been acknowledged by a large number of studies [15–24]. Many researches have employed this relationship to forecast the electricity demand at hourly, daily and weekly time-steps [23–27]. In this study, we establish this relationship based on Shanghai's data and employ the relationship to estimate the extent of power shortage gap for 1 °C increase in daily maximum temperature during heat wave. We call this extent of power shortage gap the Marginal Shortage Gap (MSG). In a standard Input–Output (I–O) model, a change in final demand would stimulate changes in output and incomes across all economic sectors via a multiplier mechanism. However, an electricty rationing at the scale of the MSG in a specific sector leads to a constraint to the production activities in the sector and as a consequence, output of this sector will not automatically expand or shrink in direct proportion to changes in final demand. This means that the standard I–O model needs to be modified to incorporate supply constraints associated with the rationing, permitting a more realistic evaluation of multiplier effects across the economy [28], as we will present in details in Section 2.3. In addition to evaluating the direct and indirect impact on sectoral outputs, it is also important to estimate the changes in CO_2 emission induced by the above magnitude of electricty rationing. For the latter purpose, we extend the I–O model with a vector of sectoral CO_2 emissions coefficients and this leads to an environemtally-extended I–O model [29–31].

We take Shanghai in China as an illustrative example to demonstrate the usefulness of this coupled modeling tool. We show that this tool is capable of quantitatively estimating the overall economic effects and carbon emissions consequences which a given magnitude of power rationing as measured by the MSG in a specific sector can impose to all sectors. Based on these estimations, we can rank individual economic sectors by (a) the total GDP loss, (b) total reduction of CO_2 emissions, and (c) the ratio of (a) to (b), as triggered by the given extent of power rationing in the sector. The availability of such information would enable decision makers to plan an electricity rationing regime at the sector level to meet the double criterions of minimizing the overall economic losses and maximizing the extent of carbon emissions reduction.

Although the concept of adaptation to climate change has received increasing attention in recent years, for heat waves, anticipatory adaptation is not common as governments and power companies are not willing to expend effort or money without clear warnings of risks or obvious losses [4]. This paper provides a simple and effective tool for decision makers in governments and utility companies to clearly assess the direct and indirect losses of a MSG shock to each individual sector of the economy. This makes it much easier for government agencies and utility companies to design short-term adaptation measures before and during a heat wave. To the best of our knowledge, there is no comparable work in the literature and this means that our work fills in an important niche in the field of applied energy.

2. Materials and methods

2.1. Daily weather and electricity data

Daily maximum temperature data are the observation records of Xujiahui Meteorological Observatory Station [32]. Xujiahui Station is located in one of commercial centers of Shanghai. It was the first Meteorological Observatory Station in East Asian and has followed the highest standard in its operation. We take July 1st to August 31st in 2007 as the illustration period for two reasons. First, heat waves occurred frequently during these two months. Second, the latest input–output table publicly available for Shanghai is the 2007 table. The daily electricity consumption and peak-load data are from the State Grid Shanghai Municipal Electric Power Company [8].

2.2. Input–output table and CO_2 emissions data

The 2007 input–output table with 144 sectors is obtained from the Survey Office of the National Bureau of Statistics in Shanghai [7]. The I–O table reports the final consumption and value added for each of the 144 sectors, as well as the inter-sectoral supply and intermediate use matrix. The CO_2 emissions data for Shanghai are calculated based on the Yearbook of Shanghai Energy Statistics and the IPCC reference approach [33,34], with China-specific emission factors being used [29–31] instead of the IPCC default value as described in [30]. The CO_2 emissions data cover 44 sectors. Therefore, we established a matching procedure to link the two datasets.

[1] For example, during a two-week event of a heat wave in California in July 2006, Pacific Gas and Electric Company (PG&E), the biggest power company in the state, reported that heavy electricity use and ambient temperature heated the transformers and they failed to cool. This in turn tripped circuit breakers, broke fuses and burned the insulation, causing short circuits inside the transformers. In northern California, 1.2 million PG&E customers experienced electricity shortages when 1150 distribution line transformers failed to cool down and stopped operating [3,5,6].

For presentation convenience, we report results for these 44 aggregated sectors. The results for 144 sectors are also available upon request.[2]

2.3. Mixed I–O model with supply constraint

The basic I–O model presents the state of an economy during a single accounting period (generally a year) and enables to analyze the changes from one state to another as triggered by exogenous shocks. Dealing with discrete and explicit changes in economic structure through rigorous accounting constitutes the most distinguished feature of I–O modeling. This feature makes I–O model powerful in evaluating the direct and indirect impacts of alternative policy options, in dealing with contingencies and shocks, across all sectors of the economy. Through the evaluation of alternative policy options and by pinpointing the inadequacies and inconsistencies in some of the options, as a basis for improving them, policy evaluation based on I–O modeling can stimulate new insights in the search for the most promising policy choice.

In the standard I–O model, changes in the exogenously given vector of final demand (Δy) are driving the economy via a matrix of output multipliers, i.e., the Leontief inverse $(I-A)^{-1}$, leading to changes in sectoral output (Δx):

$$(I-A)^{-1}\Delta y = \Delta x \tag{1}$$

To calculate CO_2 emissions triggered by Δy, we extend the I–O model in Eq. (1) with a vector of sectoral CO_2 emission coefficients e, which is defined as CO_2 emissions per unit of economic output in individual economic sector $(1, \ldots, n)$:

$$e = [e_1, e_2 \ldots e_n] \tag{2}$$

Thus, the total change in CO_2 emissions triggered by Δy can be calculated by:

$$\Delta CO_2 = e(I-A)^{-1}\Delta y \tag{3}$$

It is worth noting that the standard I–O model assumes that the economy adjusts, within the given statistical year, to changes in spending patterns. All production activities are assumed to be endogenous and demand-driven, owing to the assumed excess capacity throughout the economy. Supply is assumed to be perfectly elastic in all sectors, and a change in demand is sufficient to stimulate changes in output and incomes across other sectors. However, in the case of this study, it is clear that the sector with power rationing will not automatically expand or shrink its output level in direct proportion to changes in final demand. A direct application of Eq. (1) in this case would provide multiplier estimates that are unrealistically large due to the simple assumption on supply response. To accommodate supply constraint caused by electricity rationing, we adopt the mixed I–O model with supply constraint as developed in [35,36]. The basic setup of such a mixed model is given by

$$\begin{bmatrix} X_{no} \\ Y_{co} \end{bmatrix} = \begin{bmatrix} P & 0 \\ R & -I \end{bmatrix}^{-1} \begin{bmatrix} I & Q \\ 0 & S \end{bmatrix} \begin{bmatrix} \bar{Y}_{no} \\ \bar{X}_{co} \end{bmatrix}. \tag{4}$$

The sub-matrices in Eq. (4) are defined as follows.

P is the $k \times k$ matrix containing the elements from the first k rows and the first k columns in $(I-A)$, and represents average expenditure propensities of non-supply constrained sectors. The sectors have been labeled so that the first k sectors indicate the endogenous elements and the last $(n-k)$ sectors are the exogenous sectors.

R is the $(n-k) \times k$ matrix containing elements from the last $(n-k)$ rows and the first k columns of $(-A)$ and represents average expenditure propensities of non-supply constrained sectors on supply constrained sector output.

X_{no} is the k-element column vector with elements x_1 through x_k, representing endogenous total output of non-supply constrained sectors.

Y_{co} is the $(n-k)$-element column vector with elements y_{k+1} through y_n, representing endogenous final demand of supply-constrained sectors.

Q is the $k \times (n-k)$ matrix of elements from the last $(n-k)$ rows and first k columns of $(-A)$ matrix, and represents supply constrained sector expenditure propensities on non-supply constrained sector output.

S is the $(n-k) \times (n-k)$ matrix of elements from the last $(n-k)$ rows and columns of – $(I-A)$, and represents average expenditure propensities among supply-constrained sectors.

$\bar{Y}_{no}$ is the k-element column vector of elements y_1 through y_k, representing exogenous final demand for non-supply constrained sectors.

$\bar{X}_{co}$ is the $(n-k)$-element column vector of elements x_{k+1} through x_n, representing exogenous total output for supply constrained sectors.

In above explanation of Eq. (4), n stands for the total number of sectors in the input–output table, k refers to the number of the power rationing sectors.

In terms of our study, $\Delta\bar{Y}_{no}$ corresponds to the change in the final demand of electricity supply sector caused by exogenous shock of a heat wave, and is calculated as the difference between peak-load in the heat wave and peak-load without the heat wave. We assume there is no exogenous change of final demand in other sectors. $\Delta\bar{X}_{co}$ represents the direct output reduction of the sector which is under power rationing. We will impose power rationing at the scale of MSG sector by sector. X_{no} refers to the output change of the non-power rationing sectors induced by the indirect impact of the power rationing. Because the power supply of the electricity generation sector reaches the maximum capacity during the heat wave, the extra power needs will show up as negative numbers in the accounting system. Y_{co} stands for the final demand change of the power rationing sectors

2.4. Setting for evaluating electricity rationing choices across economic sectors

The electricity rationing plan is designed to handle the situation when electricity demand increases significantly owing to a heat wave shock and the demand surpasses the maximum power supply capacity at an interval around the peak. In order to mitigate the adversary impact of a heat wave on human health and to save human lives, electricity use for cooling residential and working spaces will not be targeted for rationing. In order to maintain the safe functioning of the city systems, electricity supply to several key sectors such as food, water and energy supply, public transportation, and medical and educational services will not be rationed. As a consequence, the rationing plan is designed to target industrial sectors.

Because there was no record of a daily power shortage, we calibrated a proxy measurement as follows. We run a linear regression between daily power use and daily maximum temperature over all work-days in July and August in 2007 and take the slope coefficient of the regression model as the proxy measure of the marginal shortage gap (MSG) in response to 1 °C increase in daily maximum temperature during a heat wave. Section 3.2 will report the result of this regression and its statistical reliability. We also convert MSG into monetary value based on average electricity

[2] To evaluate the effects of a MSG shock for each of the 144 sectors, we disaggregate the emission data to match the I–O sectors instead of aggregating I–O sectors.

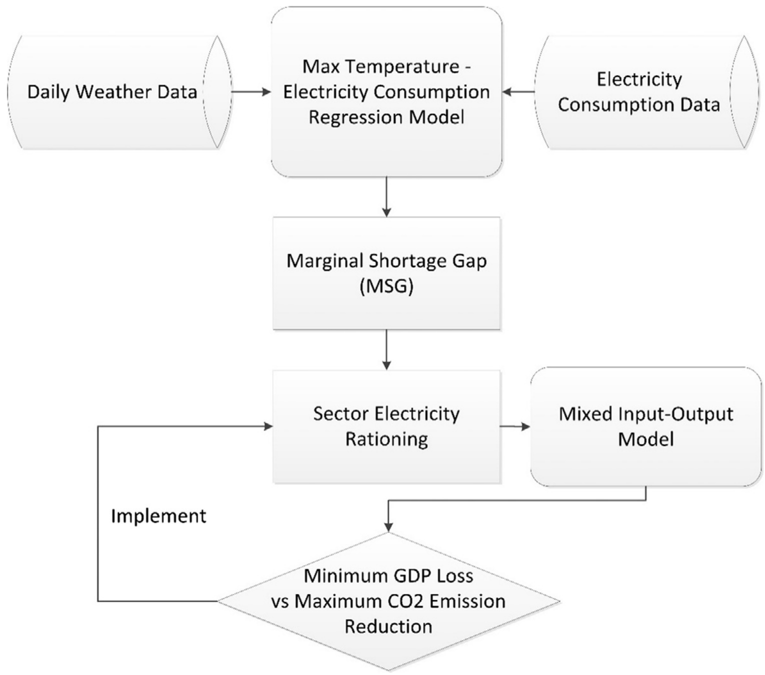

Fig. 1. Flowchart of the evaluating procedure.

price for its convenient use in the mixed I–O table. By imposing an MSG shock to the mixed I–O model (Eq. (4)) and run the rationing loop across industrial sectors, we can rank industrial sectors in terms of (a) the magnitude of total GDP loss (economic cost), (b) the extent of total CO_2 emissions reduction (environmental gain), and (c) the ratio between GDP loss and emissions reduction (economic cost of environmental gain), respectively, as triggered by the MSG shock. Fig. 1 presents the flowchart of this evaluation procedure.

2.5. Limitation of the method

Two limitations to our evaluating method are worth mentioning. First, the fixed technical coefficients of the *A*-matrix in our mixed I–O model with supply constraint imply that the amount of electricity input for producing one unit of sectoral output is fixed and will not change during a heat wave. This may lead to an overestimation of economic losses triggered by a heat wave because some end-users may switch to less electricity-intensive ways of working (e.g., more intensive utilization of underground spaces for office work and storage). However, the extent of such electricity saving is limited. Second, we do not explicitly take into account the possible reduction of power-supply capacity caused by the adversary effects of a heat wave on electricity generation, transmission and distribution system. This omission may lead to an underestimation of the extent of power-shortage. This limitation can be overcome with the help of technical data from the power generation, transmission and distribution system.

3. Results and discussion

3.1. Daily maximum temperature and electricity use regression

We run two regressions, one between daily electricity use and daily maximum temperature and the other between daily peak load and the maximum temperature over work-days during July and August in Shanghai. While both regressions are statistically well-performed, the first regression produces a higher R^2 value at 0.761, in comparison with a R^2 value of 0.719 from the second regression. Therefore, we employ the first regression. Fig. 2 presents the scatter plot and the fitted line of the first regression. The figure indicates a close association between daily electricity consumption and maximum temperature. Such a close association was clearly owing to the electricity demand for cooling residential and working spaces in a very hot summer when the average of daily maximum temperature was 34.4 °C and the highest value of daily maximum temperature was 39.5 °C. The slope coefficient of the fitted line is 8.47, indicating that a 1 °C increase in daily maximum temperature typically requires an additional power supply of 8.47 million kW h, which amounts to about 2.3% of the average daily electricity consumption over July and August in 2007. We take 8.47 million kW h as the MSG in our simulations.

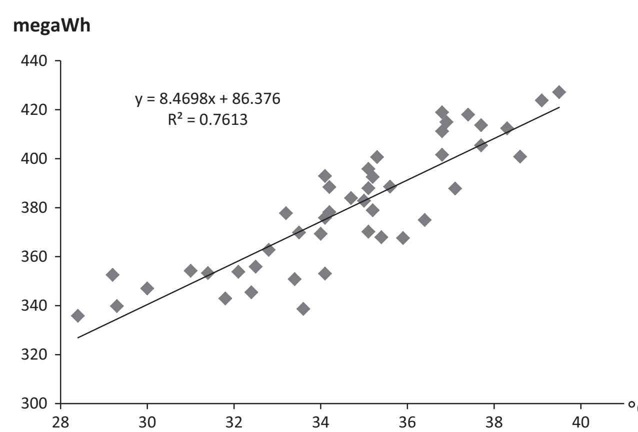

Fig. 2. Linear regression between daily electricity use and daily maximum temperature (p-value < 0.001).

3.2. Electricity consumption and CO_2 emissions in 20 industrial sectors

As discussed in Section 2.2, the sectoral match between the I–O table and list of CO_2 emission inventories results an aggregate I–O table with 44 sectors. After excluding those critical for the safe functioning of city systems, 20 industrial sectors are identified

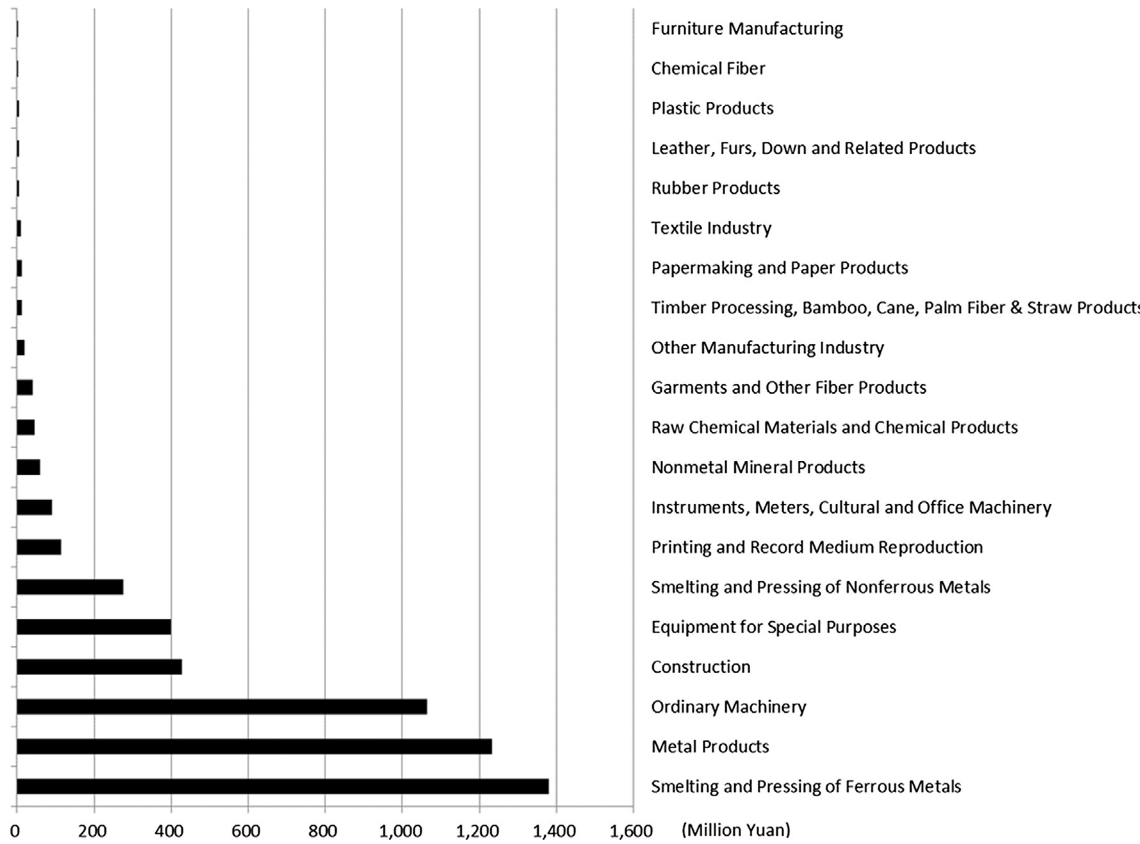

Fig. 3. Monetary value of electricity use as intermediate input in each of the 20 industrial sectors in 2007.

for potential implementation of electricity rationing, as listed in Fig. 3.

Fig. 3 shows the monetary value of electricity use as intermediate input in each of the 20 industrial sectors targeted for potential power rationing. The values range from 3.1 million to 1.4 billion Yuan. The top three sectors are Smelting and Pressing of Ferrous Metals, Metal Products, and Ordinary Machinery, with a value of power consumption over 1 billion Yuan per annum. Fig. 4 reports the share of electricity purchase in the total sectoral output across these 20 sectors. It can be seen that the Metal Products sector is most electricity-intensive, where electricity purchase accounts for 1.32% of the total sectoral output, followed by the sector of Smelting and Pressing of Ferrous Metals, with a share of 0.75%.

The total CO_2 emissions of Shanghai was 200 million tons in 2007. Direct emissions from these 20 industrial sectors accounted for about 25% of the total emissions or 51.7 million tons. As shown in Fig. 5, the top five emission sectors are Smelting and Pressing of Ferrous Metals, Nonmetal Mineral Products, Construction, Raw Chemical Materials and Chemical Products, and Ordinary Machinery. The Smelting and Pressing of Ferrous Metals sector was by far the largest emitter and directly emitted 37.4 million tons of CO_2 in 2007, which accounted for 72.3% of the total emissions from these 20 industrial sectors and 18.7% of the city total emissions. Table 6 ranks these 20 industrial sectors by CO_2 emissions intensity, which is measured by direct emission quantity per unit of sectoral output. It shows that the Smelting and Pressing of Ferrous Metals and Nonmetal Mineral Products were the most emission-intensive sectors, with an intensity level as about 204 and 130 thousand tons per million Yuan, respectively. At the ranks 3–5 were the Textile, Papermaking and Paper Products, and Other Manufacturing, with an emission intensity above 100 thousand tons per million Yuan Fig. 6.

3.3. Evaluating economic loss versus environmental gain across industrial sectors

We run the MSG-based rationing loop across industrial sectors as presented in Section 2.4. The results show that for 14 sectors among the 20 industries, in each of them the direct output loss caused by this MSG-based rationing is greater than its average daily output. This implies that a complete shut-down of the sector for one day would be insufficient to solve the shortage problem on the day. We exclude these 14 sectors from the priority list of power rationing. The remaining sectors include Raw Chemical Materials and Chemical Products, Construction, Nonmetal Mineral Products, Smelting and Pressing of Ferrous Metals, Ordinary Machinery, and Equipment for Special Purposes.

The total GDP loss triggered by the MSG-based rationing in each of the above selected 6 sectors is presented in Fig. 7. A comparison across Figs. 3, 5 and 7 shows that while the Smelting and Pressing of Ferrous Metals is the largest sector in terms of electricity use as intermediate input (Fig. 3) and direct CO_2 emission (Fig. 5), it takes only the number 4 position in Fig. 7, which ranks the 6 priority sectors from the least to the largest GDP loss as triggered by the MSG-based rationing in each of the sectors. The previous practices in Shanghai often regarded this sector as the priority target for power rationing owing to its top position in Figs. 3 and 5. Our result in Fig. 7 suggests that if a power rationing at the scale of the MSG were imposed on the Raw Chemical Materials sector rather than the Smelting and Pressing of Ferrous Metals, the total GDP loss could be reduced by 85 million yuan, which is a significant saving for one day.

The reduction of CO_2 emissions triggered by the MSG-based rationing in each of the 6 sector is presented in Fig. 8. Because the Smelting and Pressing of Ferrous Metals sector is by far the

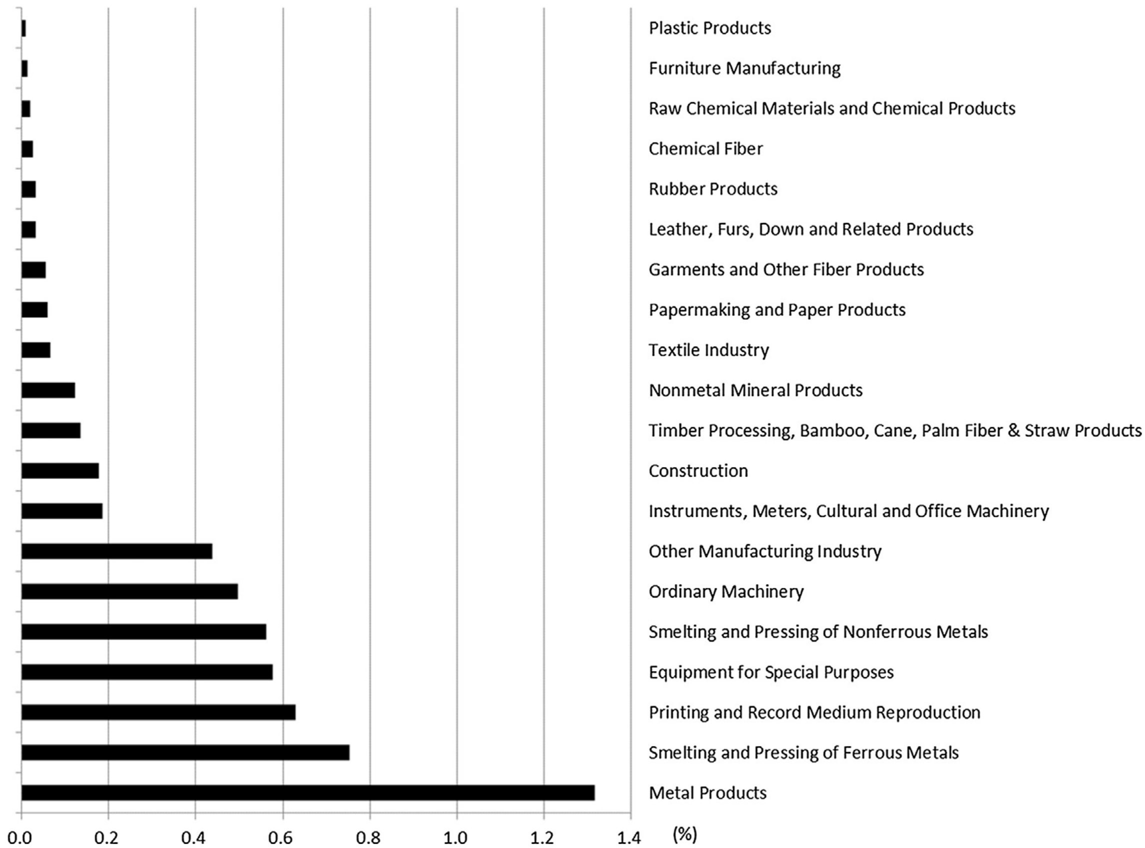

Fig. 4. Share of electricity purchase in the total sectoral output in 2007.

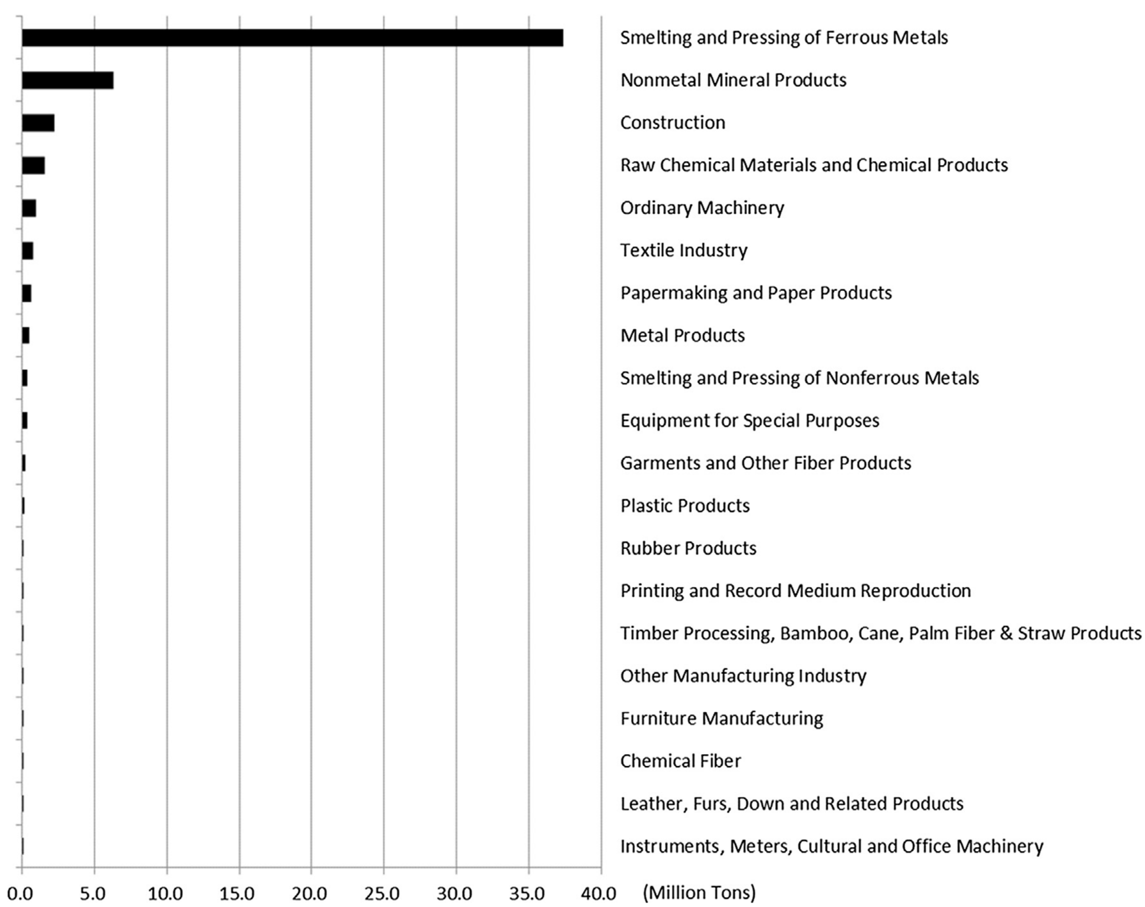

Fig. 5. Direct CO_2 emissions from each of the 20 industrial sectors in 2007.

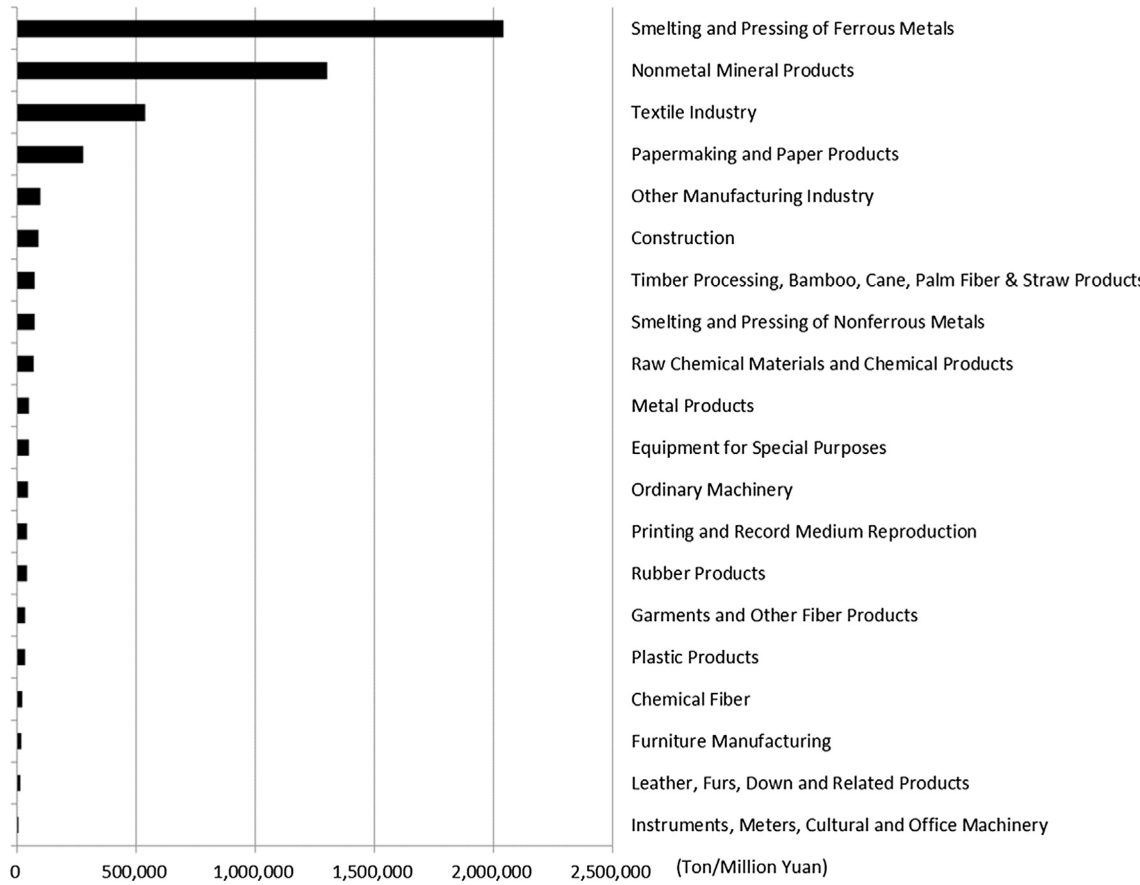

Fig. 6. CO_2 emission intensity in the 20 industrial sectors in 2007.

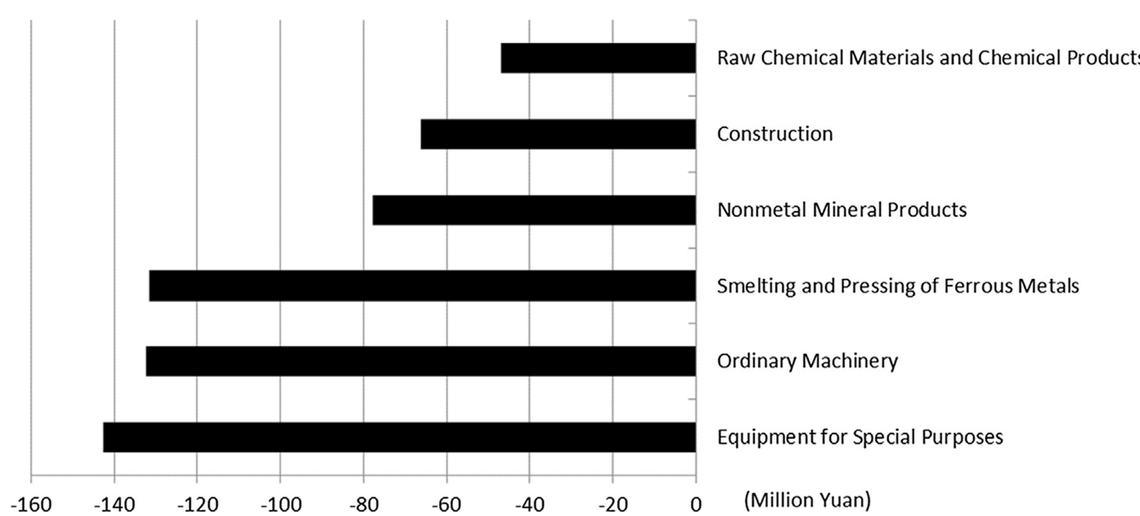

Fig. 7. Total GDP loss triggered by MSG rationing in 6 sectors.

largest sector in term of direct CO_2 emissions (Fig. 5), it is not a surprise that the greatest reduction of 42,000 tons can be triggered by a power rationing at the scale of MSG in this sector. The number 2 sector in Fig. 8 is Nonmetal Mineral Products, and this is consistent with its rank in Fig. 5. Interestingly, while the Ordinary Machinery sector ranks number 5 in Fig. 5, it moves to number 3 in Fig. 7. This move-up can be attributed to the fact that the up-stream and down-stream industries of this sector are relatively more CO_2 intensive and this results in a significant reduction in terms of indirect CO_2 emissions.

Although the issue on how to effectively coordinate the policy choices based on the different ranks in Figs. 7 and 8 are subject to political consideration of the local planners, based on our research findings we can propose a simple indicator which can help decision-makers to evaluate the economic cost of emissions reduction as triggered by a given degree of electricity rationing.

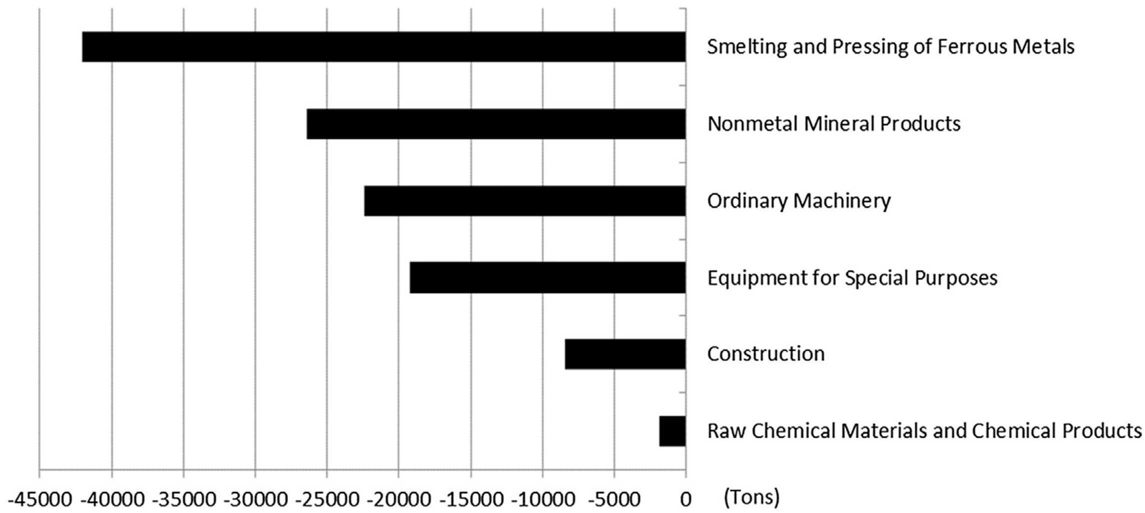

Fig. 8. The reduction of total CO_2 emissions triggered by MSG power rationing in 6 sectors.

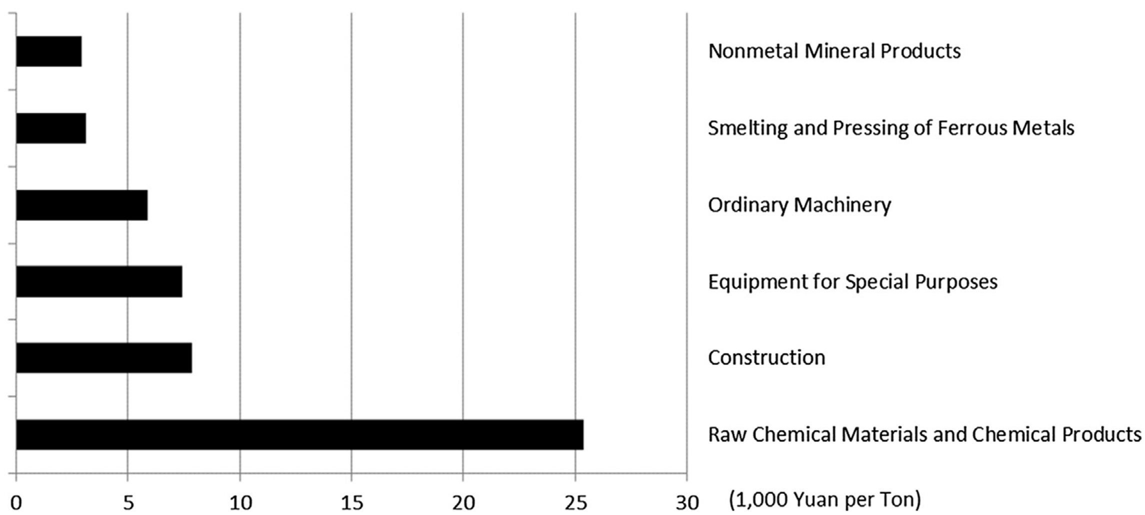

Fig. 9. Ratio of GDP loss to the reduction of CO_2 emissions in 6 sectors.

This indicator is the ratio of the total GDP loss to the reduction of total CO_2 emissions (thousand Yuan/ton) as triggered by the rationing. Fig. 9 reports this ratio for the 6 priority sectors for power rationing. It shows that the power rationing in the Nonmetal Mineral Products sector results in the lowest economic cost of CO_2 reduction at 2900 yuan/ton, followed by the Smelting and Pressing of Ferrous Metals sector and Ordinary Machinery sector, at 3100 and 5900 yuan/ton, respectively. In contrast, the rationing in the Raw Chemical Materials and Chemical Products sector results in the highest economic cost of CO_2 reduction at 25,400 yuan/ton, which is about 9 times higher than the figure triggered by the rationing in the Nonmetal Mineral Products sector.

4. Concluding remarks

Three great challenges of the 21st century for many megacities in the world are maintaining sustainable economic growth, fostering low-carbon development, and managing climate change. While failure on any of them would lead to failures on the other two, a well-constructed response to one can provide great advantages and opportunities for the others. This research aims to facilitate a well-constructed short-term electricity rationing regime for managing electricity shortage caused by heat wave shocks. The regime should eliminate the shock incidents of blackouts and brownout, minimize the overall economic cost of the electricity rationing, and maximize the environmental gain of the rationing. We have proposed a policy support tool which combines a regression model between daily electricity use and maximum temperature over the summer months and a mixed input–output model with supply constraint. We applied this tool to the datasets of Shanghai in China and ranked individual industrial sectors of Shanghai according to (a) the total GDP loss, (b) total reduction of CO_2 emissions, and (c) the economic cost of emissions reduction, as triggered by a given degree of electricity rationing enacted in the sector. These results on ranks and the magnitudes of losses and gains will provide scientifically integrated information for the local planners to effectively identify priority policy choices and coordinate policy actions in line with their political consideration and value judgement. Given the concern in the literature that for heat waves, anticipatory adaptation is not common owing to the lack of simple and effective tools to clearly assess the risks and losses caused by a heat wave [4], our work fills an important niche in the field of applied energy.

It is worth noting that the prerequisite for applying this tool is the availability of well-constructed input–output table at the city level and the table should not be behind the current year for more than five years because some technical coefficients may experience significant change after five years. Although this prerequisite may form a hard constraint for the applicability of this decision supporting tool in many cities, it is highly possible that the rapid progress in big-data collection, consolidation, and analytics would make such input–output tables widely available in near future.

Acknowledgments

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