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Estimating the marginal cost of reducing power outage durations in China: A parametric distance function approach

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ABSTRACT

The increasing penetration of intermittent renewables and the accelerated climate change are challenging the power system operation in China, and understanding the cost of reducing power outage durations is essential in supporting the equipment maintenance, infrastructure investments and regulation policies. Therefore, this study first uses production theory combined with a parametric distance function approach to estimate the marginal costs (MCs) of reducing power outage durations by 1 h. Then, we establish a fixed-effects panel data model to investigate the impacts of different environmental factors on the estimated MCs. Finally, the estimated MCs are applied to the evaluations and designs of interruption compensation prices in the demand response mechanism. The significant findings are that: (1) The national MC shows an increasing trend during the period from 2002 to 2017 in China, ranging from 1.27 billion yuan/hour to 11.63 billion yuan/hour. (2) The MCs vary substantially among different provinces, and provinces with better reliability levels will have higher MCs. (3) The current compensations for power outages are only about 6% to 61% of the estimated MCs, indicating that grid companies would like to pay for the compensations rather than to enhance the system reliability from the supply side.

1. Introduction

Electricity interruptions are perceived as significant obstacles to do business in economies worldwide, occurrence of power outages can result in serious damages to sensitive equipment, spoiled perishable goods, and productivity losses. According to the 2016 World Bank Enterprise Surveys, 12% of the business owners in developing economies regard reliable and accessible electricity as the biggest obstacle for their activities (World Bank, 2017). Well-functioning electricity supply infrastructure is also deemed as one of the main pillars of a country's competitiveness, many countries have enjoyed significant economic growth from the quality improvements in electricity supply (World Economic Forum, 2020). With the accelerated climate change, rising integration of intermittent renewables and more frequent cyber attacks, power outages have become severe challenges for the economic development and social stability (Aklin et al., 2016; Al-Omari et al., 2021; Cohen et al., 2018). To meet the increasing needs of electricity supply quality, grid companies have to enhance the operations and maintenance ability, to install more monitor and control equipment, and to invest into new transmission and distribution lines (Baarsma and Hop, 2009; Chen et al., 2021; Morrissey et al., 2018b). Therefore, a good knowledge of the marginal costs (MCs) of reducing power interruption durations is needed to achieve an optimal trade-off between different operational targets (cost savings and high reliability) of grid companies (Küfeoğlu et al., 2018; Lacommare and Eto, 2006). The information of MCs is not only crucial for the cost-benefit analysis of different quality improvement measures but also necessary for the regulators in setting penalties/rewards based on the predetermined quality targets (Giannakis et al., 2005; Ozbafli and Jenkins, 2016).

Although the quality of power supply has long been regarded as a vital regulation area of electricity utilities, quantifying the cost of reducing power outage durations is a challenging task (De Nooij et al.,

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2007). On the one hand, there is no market in which the power-supply interruptions are traded, so the MCs of quality improvements cannot be observed directly (Amoah et al., 2019). On the other hand, power system operation is a system engineering which relies on the well-functioning and coordination of different inputs (electricity infrastructure, labor resources, and capital inputs), so it is not easy to separate the power quality-related cost from other cost (Zachariadis and Poullikkas, 2012).[1] Several studies have pioneered in estimating the cost of reducing power outage durations, but most of them focused on the developed and high-income countries (Amoah et al., 2019). There are a few relevant pieces of evidence for China, which has the largest electricity supply system in the world. In 2018, the electricity generation in China accounted for 26.72% of the world's total electricity generation (British Petroleum, 2019). Moreover, China's System Average Interruption Duration Index (SAIDI) is much higher than that of the developed countries (see Fig. 1). The SAIDI of China in 2019 is 13.72 h per household annually, while the average value of other benchmarked countries is only 1.23 h per household. Therefore, China's grid companies have more desire to improve the supply quality considering this big gap.

To provide guidance for the electricity reliability improvement policies, this study plans to estimate the cost of improving power system quality in China, aiming at answering the following three questions:

(1) What are the MCs of reducing power outage durations in China? How do they change temporally, and what are the regional differences?
(2) How are the MCs affected by different environmental factors?
(3) How can the estimated MCs be used to design the electricity reliability policies?

To answer the above three questions, this study firstly uses production theory combined with a parametric distance function approach to estimate the MCs of reducing electricity outage durations. Then, we develop a fixed-effects panel data model to explore the impacts of different environmental factors on the estimated MCs. Finally, the estimated MCs are applied to the evaluations and designs of interruption compensation prices in the demand response mechanism. This study contributes to the existing literature from the following two aspects. On the one hand, most of the existing studies focus on estimating the impacts of power outages from a demand side perspective, few studies have estimated the MCs of reducing power outage durations from the supply side, especially for the developing countries. Our study can bridge this gap and provide quantitative evidences for the cost-benefit analysis of different quality improvement measures. On the other hand, the estimated MCs are used to the support the implementation mechanism design of demand side response in China, which can help coordinating the electricity reliability policies from both the supply side and the demand side.

The remainder of this paper is organized as follows. Section 2 surveys the literature that uses different methodologies to estimate the cost of reducing power outages. Section 3 illustrates the estimation model of MCs, the impact factor analysis model and the data. Section 4 shows the results and discussions. Section 5 summarizes the conclusions and proposes policy implications based on the result analysis.

2. Literature review

The cost of improving electricity supply quality is necessary information for the power system planning, regulation mechanism designs, and electricity interruption compensations (Jamasb et al., 2012; Ovaere et al., 2019). Estimating the cost of power outages is also an attractive field for researchers, but the method selections depend on the perspectives (supply-side and demand-side) taken in the estimation process (De Nooij et al., 2007). Most of the existing studies choose to quantify the reliability cost from the demand side, which estimates the economic impacts of electricity interruptions on different types of consumers (Hashemi et al., 2018; Praktiknjo et al., 2011; Reichl et al., 2013). Customer surveys (Willingness to Pay/Accept), indirect analytical approaches (macroeconomic approaches) and case studies (direct cost estimation) are the three popularly used methods from the demand side perspective (Amoah et al., 2019; Diboma and Tatietse, 2013; Küfeoğlu et al., 2018; Küfeoğlu and Lehtonen, 2016; Kim and Cho, 2017; Munasinghe and Sanghvi, 1988; Schröder and Kuckshinrichs, 2015). The cost estimations from the supply side are relatively less, but they cannot be neglected in the cost-benefit analysis of different quality improvement measures. This is because the cost of reducing power outage durations or frequencies can provide necessary decision making support for the grid companies to invest into new infrastructure and upgrade equipment. The existing literature which assesses the cost from the supply side can be classified into the following two categories.

The first category is a production function-based approach, which originates from the microeconomic production theory. This method has already been widely used in estimating the MCs of carbon emissions, air pollutant emissions, and water leakages (Färe et al., 2006; Hailu and Veeman, 2000; Molinossenante et al., 2016; Peng et al., 2018; Wei et al., 2013). This parametric approach firstly defines a multi-input/multi-output production function of electricity utilities, which are usually expressed in the form of distance functions. The parameters of production functions are then estimated by either parametric methods or non-parametric methods. Based on the estimated production functions, the MCs can be derived according to the substitution property between different inputs (Färe et al., 2006). The cost of power quality improvement can be estimated based on different indicators, which include the outage durations, the outage frequencies, the total kWh of electricity outages and the interrupted customers (Morrissey et al., 2018; Küfeoğlu et al., 2018; Yu et al., 2009). For example, Coelli et al. (2013) estimated the MCs of preventing one interruption in France for the period of 2003-2005 by using an input distance function approach. Küfeoğlu et al. (2018) developed an input distance function model to quantify the MCs of reducing outage durations (1 min) of 78 distribution network operators in Finland between 2013 and 2015. Jamasb et al. (2012) proposed a new framework to estimate the MCs of reducing electricity distribution losses in the United Kingdom (UK).

The second category is an estimation approach based on various outage preventative measures. To prevent the occurrence of power outages, grid companies or consumers will deploy back-up generators, distribution automation (DA) systems, and other preventative measures. Using econometric techniques or direct accounting methods, the MCs can be inferred based on the caused cost of these preventative measures and the changes of outage durations. Beenstock (1991) proposed a theoretical model to calculate the cost of reducing power outages based on the cost of back-up generators. Ghajar (1998) estimated the cost of reducing power outages on account of the operating reserves in Lebanon. Adenikinju (2003) quantified the cost of reducing power interruptions in 1998 based on the provision of back-up auto-generation facilities. Su and Teng (2007) analyzed the cost of reducing power outage durations based on the DA systems and further used it for the cost-benefit analysis of quality improvement measures. Jamasb et al. (2012) developed an econometric approach to estimate the MCs of reducing customer minutes lost in the UK from 1995 to 2003, with consideration of the corrective cost of power outages. Oseni and Pollitt (2015) established an econometric model to quantify the cost of reducing power outages by comparing the firms with or without back-up generators.

These two approaches have both advantages and drawbacks.

[1] Blackouts and power interruptions occur due to the component outages, demand uncertainty, intermittent supply, adverse weather, equipment failure, human error, vegetation management practices, etc.

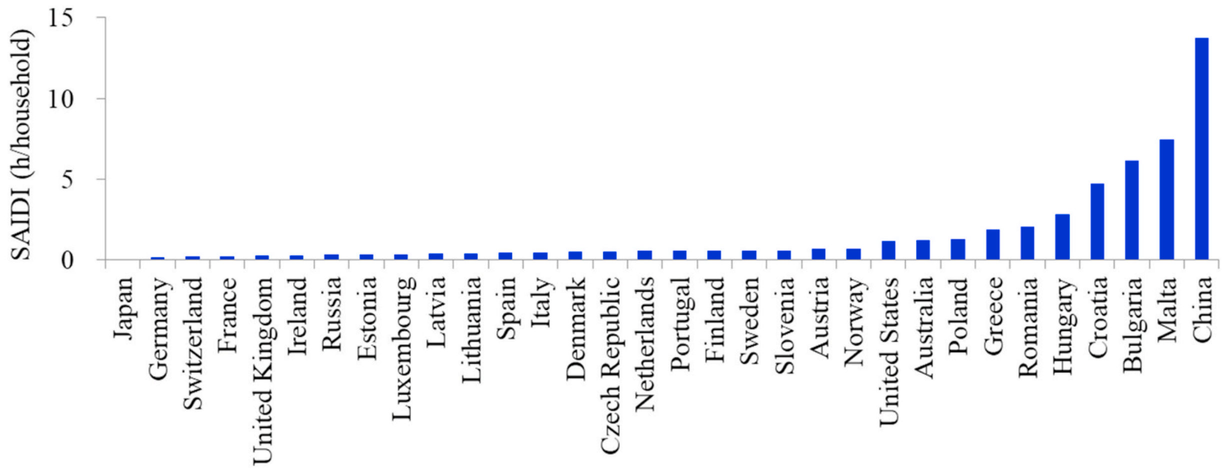

Fig. 1. The international comparison of SAIDI values in 2019.
Notes: the SAIDI values in this figure consist of both the planned and unplanned power outages. The data of China is drawn from National Energy Administration (NEA), while the data of other countries are obtained from World Bank.

Production function-based approach is relatively straightforward and easy to apply. Moreover, it is relatively mature because many studies have employed this approach to estimate the MCs of reducing different inputs and outputs in various production activities. However, it can only provide broad and average results through benchmark analysis among similar production units, and are not applicable for a specific outage event. The approach based on outage preventative measures is more case-specific and can provide component details of the outage cost, but it requires comprehensive statistical information of the outage events which is not often easy to be obtained. Based on the data availability, we decide to use the production-function based approach in this study. Compared with existing studies, this paper makes two contributions in estimating the cost of reducing power outage durations. This study, to the best of our knowledge, is the first study to estimate the MCs of reducing 1 h of power outages in China at the provincial level, which can provide scientific support for the decision-makings in the electricity quality improvement. Secondly, the estimated MCs are applied to the evaluations and designs of interruption compensation prices in the Demand Response (DR) mechanism. This is a novel application of the estimated MCs of reducing electricity interruption lengths, which can coordinate the reliability policies from the two sides (supply and demand).

3. Methodology

3.1. Estimation model for the marginal cost of reducing power outage durations

Grid companies have a multi-input, multi-output production process, and their production set can be defined by equation (1). $\mathbf{x}$ is a vector of input variables, while $\mathbf{y}$is a vector of output variables. Although the variable selections are key in estimating the production functions, there is no strict rule for the variable choices. They are determined by a combination of the research purpose and data availability (Jamasb and Pollitt, 2001). On the input side, both the physical and monetary variables can be selected as input variables, and the popular input variables consist of capital stock, operational and maintenance cost, grid line length, and transformer capacity (Coelli et al., 2013; Growitsch et al., 2009). As from the output side, the frequently considered variables include electricity deliveries and the number of consumers (Deng et al., 2017; Jamasb and Pollitt, 2001). In order to assess the MCs of reducing power outage durations, SAIDI is chosen as an additional input variable in this study.

$$L(\mathbf{y}) = \{\mathbf{x} \in \mathbf{R}_+^K : \mathbf{x} \text{ can produce } \mathbf{y}\} \tag{1}$$

Following Coelli et al. (2013) and Liu et al. (2019), the production process of grid companies is modeled by an input-oriented distance function ($D_I(x,y)$), see Equation (2). For every data point (x,y) within the production set, the distance function seeks to find the biggest value of ρ such that $(x/\rho,y)$ remains within the feasible production set. ρ measures the technical inefficiency of the grid company because it can produce the same output vector when the input is proportionally reduced by $1/\rho$.

$$D_I(x,y) = max\{\rho : (x/\rho) \in L(y)\} \tag{2}$$

To estimate the distance function ($D_I(x,y)$), a translog input distance function is specified for the grid companies of K inputs and M outputs during the period T, because it is flexible and easy to impose the assumptions of symmetry, homogeneity, and monotonicity, see Equation (3).

$$\begin{aligned} \ln D_i^t(x_i^t, y_i^t) \\ = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi}^t + \frac{1}{2}\sum_{m=1}^{M}\sum_{h=1}^{M} \alpha_{mh} \ln y_{mi}^t \ln y_{hi}^t \\ + \sum_{k=1}^{K} \beta_k \ln x_{ki}^t + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ki}^t \ln x_{li}^t + \frac{1}{2}\sum_{m=1}^{M}\sum_{k=1}^{K} \delta_{mk} \ln y_{mi}^t \ln x_{ki}^t \\ + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 + \sum_{m=1}^{M} \psi_m \ln y_{mi}^t t + \sum_{k=1}^{K} \theta_k \ln x_{ki}^t t \quad i = 1,2,\dots,N; t = 1,2,\dots,T \end{aligned} \tag{3}$$

Furthermore, a linear programming optimization approach, proposed by Aigner and Chu (1968), is used to estimate the parameters (α_0, α_m, α_{mh}, β_k, β_{kl}, δ_{mk}, λ_1, λ_2, ψ_m, θ_k), see Equation (4). By optimizing the parameter choices, the objective function minimizes the total deviations of the logarithmic values of the distance function from zero; Constrain (i) ensures that all production functions of grid companies are feasible and the input-output data points are located within the boundary of the production set enclosed by the production frontiers; Constrain (ii) and (iii) imposes the monotonicity assumptions on the outputs and inputs of grid companies, respectively; Constrains (iv) shows the symmetry property of the distance functions; Constrains (v) to (viii) are used to represent the translation property of linear homogeneity.

$$\begin{cases} min \sum_{t=1}^{T}\sum_{i=1}^{N}\left[\ln D_i^t(x_i^t, y_i^t) - 0\right] \\ i)\ \ln D_i^t(x_i^t, y_i^t) \geq 0 \\ ii)\ \frac{\partial \ln D_i^t(x_i^t, y_i^t)}{\partial \ln y_i^t} \leq 0 \\ iii)\frac{\partial \ln D_i^t(x_i^t, y_i^t)}{\partial \ln x_i^t} \geq 0 \\ iv)\beta_{kl} = \beta_{lk}\quad k = 1,2\ldots,K, l = 1,2\ldots,K;\quad \alpha_{mh} = \alpha_{hm}\quad m = 1,2\ldots,M, h = 1,2\ldots,M \\ v)\ \sum_{k=1}^{K}\beta_k = 1 \\ vi)\sum_{l=1}^{K}\beta_{kl} = 0,\ k = 1,2\ldots,K \\ vii)\sum_{k=1}^{K}\delta_{mk} = 0\ , m = 1,2\ldots,M \\ viii)\sum_{k=1}^{K}\theta_k = 0 \end{cases} \tag{4}$$

As pointed out by Hailu and Veeman (2000), there is a duality relationship between the input distance function and the cost function of the electricity companies. Moreover, the ratios of different inputs' MCs can be estimated by Equation (5). ω_{ki} and ω_{li} are the MCs of two inputs x_{ki} and x_{li} respectively.

$$\frac{\omega_{ki}^t}{\omega_{li}^t} = \frac{\partial D_i^t / \partial x_{ki}^t}{\partial D_i^t / \partial x_{li}^t} \tag{5}$$

Therefore, if the MC of one input variable is known, the MC of reducing electricity interruption durations (ω_{ei}^t) can be calculated based on the estimated ratios and the input distance functions. In this study, the MC of operational and maintenance cost (ω_{oi}^t) is selected and set as 1 yuan/kWh following Coelli et al. (2013), so the MCs of reducing power outage durations are calculated by equation (6).[2]

$$\omega_{ei}^t = \omega_{oi}^t \cdot \frac{x_{oi}^t}{x_{ei}^t} \frac{\beta_e + \sum_{l=1}^{K}\beta_{el}\ln x_{li}^t + \frac{1}{2}\sum_{m=1}^{M}\delta_{me}\ln y_{mi}^t + \theta_e t}{\beta_o + \sum_{l=1}^{K}\beta_{ol}\ln x_{li}^t + \frac{1}{2}\sum_{m=1}^{M}\delta_{mo}\ln y_{mi}^t + \theta_o t} \tag{6}$$

3.2. Impact factor analysis model

To improve the electricity supply quality in the future, it is also necessary to analyze how the MCs are influenced by different environmental factors. Therefore, a fixed-effects panel data model is established, as shown in Equation (7).

$$ln\ (p_{it}) = \alpha + \boldsymbol{\eta}\mathbf{X}_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{7}$$

[2] As suggested by Coelli et al. (2013), the price or the marginal cost of capital stock is more difficult to estimate. This is because it requires assumptions regarding the depreciation and interest costs, so we chose to estimate the marginal cost using the operational and maintenance cost.

Table 1
Descriptive statistics.

Indicators	Units	Mean	Std. Dev.	Max.	Min.
Outputs					
Electricity delivered (ELECTRI)	TWh	127.07	110.17	595.90	4.06
Customers (COUST)	million household	11.86	9.76	43.79	0.31
Inputs					
Capital stock (CAPITAL)	billion yuan	49.19	42.91	262.76	1.24
Operational costs (OPEX)	billion yuan	3.54	2.89	16.47	0.07
Grid lengths (LENGTH)	million m	41.19	23.32	101.89	4.37
Interruption time (NINT)	hours/ household	21.80	16.59	118.65	1.92
Environmental factors					
Maximum wind speed (SPEED)	m/s	12.24	2.04	18.88	6.45
Proportion of mountains (MOUN)	%	28.98	17.39	65.95	0.43
Annual total rainfall (RAIN)	mm	897.99	526.36	2939.70	74.90
Thunder numbers (THUNDER)	thousand times	302.31	250.51	1426.24	2.62
Maximum temperature (MAXTEM)	°C	36.88	2.80	43.00	28.90
Minimum temperature (MINTEM)	°C	-10.23	10.37	11.10	-33.30

Where p_{it} is the estimated MC of reducing power interruption lengths from Equation (7); $\mathbf{X}_{it}$ is the vector of environmental factors considered in this study; λ_i represents the provincial fixed effects and allows us to take into account the unobserved heterogeneity across provinces that is potentially correlated with their MCs; μ_t is the fixed effects of time which is used to capture time-variant unobserved heterogeneity; ε_{it} is the residual error term; α and $\boldsymbol{\eta}$ are the coefficients to be estimated. This study assumes that the impacts of environmental factors on the cost of reducing outage durations can be obtained from $\boldsymbol{\eta}$ after controlling for province fixed effects and time variant fixed effects.

3.3. Data

The empirical data of 31 provincial grid companies from 2002 to 2017 is employed to estimate the MCs of power outages in China.[3] Based on the data availability and suggestions from Jamasb and Pollitt (2001) and Growitsch et al. (2009), four input variables and two output variables are chosen to quantify the MCs, see Table 1. The data of grid line lengths, SAIDI, total number of customers, and delivered electricity are directly drawn from China Power Statistical Yearbook. The annual operational and maintenance (O&M) cost of provincial grid companies consist of the cost caused by the transmission and distribution lines and transformers, which are calculated as a result of multiplying the total

[3] The provincial grid companies of Hong Kong, Taiwan and Macao are not considered in this study due to the data availability. In addition, we do not differentiate the data of transmission companies and distribution companies because they are not vertically separated in China.

line length or total transformer capacity by their unit cost respectively.[4] The length of grid lines and transformer capacity are drawn from the China Power Statistical Yearbook, while the unit operational and maintenance cost of these electricity supply infrastructure (yuan/km for grid lines and yuan/kVA for transformers) is directly obtained from State Grid Corporation of China (2017). The capital stock data of provincial grid assets is not publicly available, so we calculate them by ourselves from the following two major steps. First, the national capital stock of grid assets is assessed using the Perpetual Inventory Method (PIM), with reference to Zhang and Zhang (2003).[5] The initial capital stock data in the base year of 2002 is obtained from the China Industry Economy Statistical Yearbook. The annual investment data of grid assets are drawn from China Fixed Assets Investment Statistical Yearbook. The depreciation rate is set at 3.8% following Liu et al. (2019). Then, the provincial capital stocks are split from the national capital stock values according to the shares of their total asset values, which are obtained from China Power Statistical Yearbook. In addition, all monetary variables in this study are expressed in 2017 prices using a deflator of gross industrial commodities prices from National Bureau of Statistics (NBS).

In the impact factor analysis of the MCs, six factors are considered in the regression model based on Anaya and Pollitt (2017), Deng et al. (2017), Andersen and Dalgaard (2013). All the selected factors are natural environmental factors and will not result in endogeneity problems, this is because the MCs don't have direct or indirect impacts on these natural environmental factors. All the six factors are the potential causes of power outages. The annual maximum wind speed (SPEED) is taken into consideration because the overhead transmission lines can be broken and the tower will be collapsed in the strong windy days. The number of thunders and lightning (THUNDER) are direct causes of outage events, provinces with higher frequencies of lightning are expected to have more power outages. Thunders and lightning can lead to the damages of electricity equipment and result in short circuit. They also account for a large share of the reasons of outage events in many countries. For example, more than half of the power outages on transmission lines are due to the lightning in Swaziland, while 65% of the over-voltage damages to the distribution networks are attributed to lightning in South Africa (Andersen and Dalgaard, 2013). The proportion of mountain areas (MOUN) in a province can affect the possibility of outages, this is because the accident of falling trees will damage the transmission lines. The annual total amount of rainfall (RAIN) is considered because it can cause natural disasters such as flood, debris flow and landslide, which will further result in power outages. The annual maximum temperature (MAXTEM) and minimum temperature (MINTEM) are also sources of power outages due to the correlation between electricity load and temperature. To reduce power outage durations from stronger shocks of natural environmental factors, the types of previous protection measures need to be changed or the intensity of measures have to be enhanced, this is because the previous cheaper measures may become ineffective to resist these stronger shocks. All of these changes will push up the cost of reducing power outage lengths in order to cope with the adverse environmental influences. Therefore, the natural environmental factors will not only affect the occurrence and

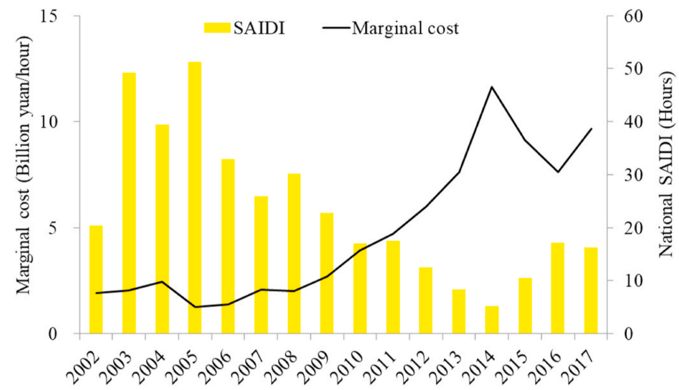

Fig. 2. The total marginal cost of reducing 1 h of power outages in China.

intensity of power outages, but also influence the cost of reducing the lengths of electricity interruptions. As to the data sources of impact factors of the MCs, the proportion of mountain area in different provinces are obtained from NBS. The data of maximum wind speed, annual rain fall, maximum temperature and minimum temperature are drawn from the data website of China Meteorological Administration (CMA).[6] The annual total thunder and lightning numbers of different provinces are drawn from CMA (2018). A summary statistics of these data is shown in Table 1.

4. Results and discussions

4.1. Marginal costs of reducing power outage durations

The established distance function model is employed to estimate the provincial MCs of reducing power outage durations for the period from 2002 to 2017. Following Färe et al. (2005), all the input and output variables are normalized by their mean values to avoid convergence in the estimation results. The national MC is calculated by summing these provincial MCs, see Fig. 2. We can see that the MC of reducing national SAIDI by 1 h generally exhibits an increasing trend during the study period, which ranges from 1.27 billion yuan/hour to 11.63 billion yuan/hour. Similar to Adenikinju (2005) and Jamasb et al. (2012), the national MCs show a negative correlation relationship with the national SAIDI values, indicating that the power quality improvements become more expensive as the networks have higher reliability. This can also explain why the rebound of SAIDI leads to a decline of the MCs after 2014.

Apart from the national MC, the spatial distribution of MCs are analyzed by taking the year of 2017 as an example, see Fig. 3. The MCs vary substantially among different provinces, ranging from Hainan (0.07 billion yuan/h) to Jiangsu (0.73 billion yuan/h). From the coincidence analysis of the MCs and the outage time, the provinces of better electricity supply reliability (Jiangsu, Shanghai, and Guangdong) have relatively higher MCs, while the less reliable provinces (Hainan, Qinghai and Jilin) have lower MCs. The differences among provincial MCs can be used for setting priority in designing the reliability improvement plan under a constrained budget. The total MC of all the provinces is equal to 9.66 billion yuan/hour. This means that, on average, all the grid companies need to spend 6.74% of their annual profits to reduce the national

[4] The methodology for calculating the O&M cost is $TOM_t = \sum_n L_t \cdot LOM_{n,t} + \sum_n T_t \cdot TOM_{n,t}$, where TOM_t is the annual total O&M cost of a provincial grid company; L_t is the total transmission and distribution line length of the voltage type $n$in a province; T is the total provincial transformer capacity of the voltage type n; Ten main voltage types of grid lines and transformers are considered in this study, including 35 kV, 110 kV, 220 kV, 330 kV, ±400 kV,500 kV, ±660 kV, 750 kV, ±800 kV and 1000 kV $LOM_{n,t}$ is the annual O&M cost of one km transmission and distribution lines; $TOM_{n,t}$ is the annual O&M cost of one kVA transformers.

[5] The PIM methodology for calculating the national capital stock of grid assets is $K_t = I_t + (1 - \alpha_t) + K_{t-1}$, where K_t is the capital stock in year$t$; I_t is the new investment in year t; α_t is the depreciation rate in year t.

[6] It is difficult to obtain the total rainfall of a province due to limited numbers of monitoring stations, so the total rainfall of a capital city in a province is used in this study.

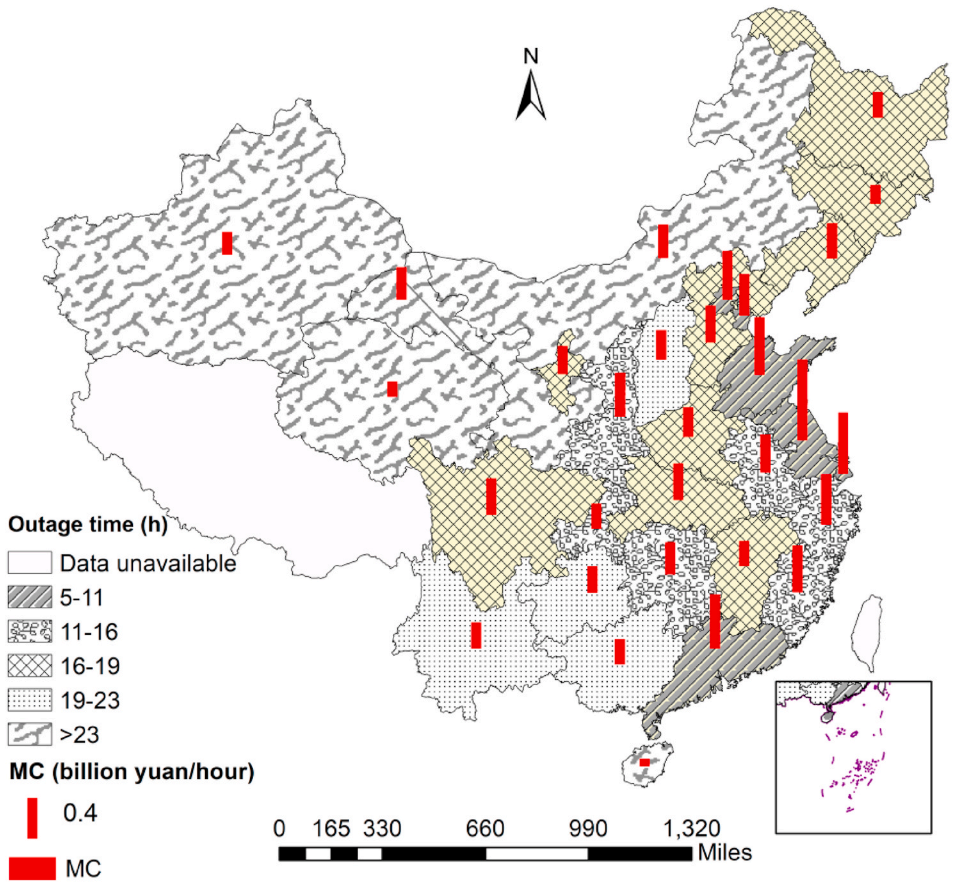

Fig. 3. Spatial distributions of the estimated provincial MCs in 2017.

SAIDI by 1 h in 2017.[7]

In addition, we have also compared our estimated results with previous studies, see Table 2. The cost of reducing power outage durations depend on many factors, such as the characteristics of the electricity system, the estimation perspectives and the used methodologies. To increase comparability among different studies, the cost of reducing 1 h of power outages per household is selected as the indicator for comparison. Moreover, these studies are classified into two categories. The first category uses the Willingness To Pay (WTP) or Willingness To Accept (WTA) to estimate the cost of reducing power outage durations from the demand side, while the second one assesses the cost from the supply side. We have also added the methodology used in these studies and the estimation year for better comparison in Table 2.

Several interesting findings can be obtained from comparing our results with that from previous studies. First, the costs in the developed countries are bigger than the cost in China. The cost per household in UK is about 29 times of China's cost in 2002, while the cost per household in France is about 32 times of China's cost in 2005. This is because the cost of reducing power outage durations depends on the system reliability levels, and the electricity supply in the UK and France are much more reliable than that in China. Second, the cost estimated from the supply side is smaller than the results from the demand side. The WTP of reducing 1 h of power outages is 2.60 $/h per household in Hubei in 2015, but the marginal cost of reducing power outage durations is only 1.71 $/h per household. This result also holds for the Shandong province in 2004. Third, regions or countries with smaller SAIDI values have higher outage cost. This can be evidenced by the fact that the cost in China in 2002 is bigger than that in 2005. In addition, since a perfect comparison among different costs of reducing power outages should keep all other things the same, more quantitative studies are needed to conduct a meaningful international comparison in the future.

4.2. Impact factor analysis of the power outage costs

The established fixed-effects panel data model is employed to investigate the impacts of different environmental factors on the estimated MCs.[8] To increase the robustness of our estimation results, six environmental factors are added to the regression model using a stepwise approach (see Table 3). The fitness of different regression models can be judged by comparing the values of Akaike Information Criterion (AIC), and the model with the lowest AIC values perform the best.

[7] In China, every province has a provincial grid company to supply electricity, the only exception is the Inner Mongolia province. The Inner Mongolia province has two provincial grid companies, State Grid Corporation of China (SGCC) is in charge of the electricity supply for the eastern part of the province, while the Inner Mongolia Power (IMP) provide electricity for the western part. China Southern Grid (CSG) supply electricity for the five southern provinces in China (Yunnan, Guizhou, Guangdong, Guangxi, Hainan), while SGCC supply electricity for the remaining 26 provinces except Hong Kong, Taiwan and Macao. All these provincial grid companies belong to three parent grid companies in China, including SGCC, China Southern Grid (CSG) and IMP. The annual profits of SGCC, CSG and IMP are 91.02 billion yuan, 49.50 billion yuan and 2.72 billion yuan respectively in 2017.

[8] The suitability of fixed-effects panel data model is also confirmed by the results from Hausman test. The details are not presented in this paper to save space, but they are available upon requested. In addition, In order to reduce the heteroscedasticity, the logarithm values of the six variables are used in the regression models except the MOUN and MINTEM. The reasons for their exceptions are that MOUN is a ratio variable and the value of MINTEM is negative.

Table 2
The international comparison of the cost of reducing power outages.

Country	Year	SAIDI (hours/household)	Outage cost (US $\$_{2017}$/household* h)	Methodology	References
Demand side					
Sweden	2017	0.72	3.02	WTP	Carlsson et al. (2021)
Denmark	2013	0.41*	4.75	WTP	Morrissey et al. (2018)
Greece	2013	1.57*	2.97	WTP	Morrissey et al. (2018)
Germany	2013	0.21*	1.23	WTP	Morrissey et al. (2018)
Netherlands	2013	0.40*	2.49	WTP	Cohen et al. (2016)
Finland	2013	0.14*	3.75	WTP	Cohen et al. (2016)
Hong Kong	2013	0.43*	47.35	WTP/WTA	Woo et al. (2014)
Hubei, China	2015	14.23	2.60	WTP	Zheng et al. (2016)
Shandong, China	2004	11.08	1.80	WTP	Zhou and Fan (2006)
China	2000	34.84**	1.31	Indirect analytical approach	He et al. (2006)
Supply side					
United Kingdom	1995–2002	2.85	48.20	Panel data model	Jamasb et al. (2012)
France	2005	1.17	22.48	Distance function	Coelli et al. (2013)
China	2002	20.41	1.67	Distance function	This study
China	2005	51.59	0.71	Distance function	This study
Hubei, China	2015	14.23	1.71	Distance function	This study
Shandong, China	2004	11.08	1.23	Distance function	This study

Notes: The exchange rates between different currencies are drawn from International Monetary Fund. All the data have been transformed to the 2017 values in US dollars using the deflator of Consumer Price Index from National Bureau of Statistics. The SAIDI values of some countries are not accessible for some specific years, so we use the data from the nearest year as a substitution. For example, the data with * indicates that we use the average value of 2013-2015 from Arlet (2017), while the data with ** indicates that we use the average value of 2002-2003.

Table 3
Estimation results of different impact factors.

Dependent variable	Model 1 ln (MC)	Model 2 ln (MC)	Model 3 ln (MC)	Model 4 ln (MC)	Model 5 ln (MC)	Model 6 ln (MC)
ln (SPEED)	0.093*** (0.030)	0.100*** (0.032)	0.095*** (0.035)	0.089*** (0.030)	0.093*** (0.031)	0.093*** (0.031)
ln (THUNDER)		0.333*** (0.084)	0.344*** (0.084)	0.336*** (0.085)	0.336*** (0.083)	0.336*** (0.083)
MOUN			0.017** (0.008)	0.016** (0.008)	0.015** (0.008)	0.015** (0.008)
ln (RAIN)				0.152 (0.126)	0.183 (0.116)	0.186 (0.116)
ln (MAXTEM)					1.060** (0.503)	1.047** (0.520)
MINTEM						0.003 (0.007)
Constant	18.161*** (0.077)	14.099*** (1.009)	13.487*** (1.092)	12.602*** (1.185)	8.597*** (2.500)	8.652*** (2.567)
Province	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Adj. R^2	0.809	0.824	0.825	0.826	0.827	0.827
AIC	1.289	1.208	1.205	1.202	1.198	1.202
Obs	496	496	496	496	496	496

Notes: standard deviations in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Obs stands for the number of observations.

Therefore, the results of Model 5 are utilized for results discussion in this study.

As seen from Table 3, the effects of maximum wind speed on the MCs are positive at the 1% significance level. In particular, a 1% increase in the maximum wind speed will increase the MC by an average of 0.093%. According to conclusions from Liu et al. (2008) and Zhu et al. (2007), wind speeds have significant impacts on the number and duration of electricity outages. The choices of different protection measures to safeguard electricity system from outages are also affected by the wind speeds. Moreover, the cost of protection measures tends to increase with the maximum wind speeds. Therefore, more expensive protection measures need to be used to further reduce the power outage durations in higher wind speed regions, such as increasing the infrastructure standards, using stronger grid line materials and building more solid foundation for electricity towers. Therefore, the increase in the maximum wind speeds will contribute to bigger costs of reducing the outage lengths.

The MCs are also significantly positively related to annual total number of thunders and lightning in a province. Specifically, the MC will, on average, increase by 0.336% if the number of lightning increases by 1%. To avoid the electricity equipment damages and short circuit from bigger frequency of thunders and lightning, more advanced and costly measures need to be taken to further reduce the power outage time, such as the establishment of a dynamic monitoring system of thunders and lightning and the reallocation of the critical electricity equipment. All of these measure deployments will increase the cost of reducing outage lengths.

Similar to the conclusions from Yu et al. (2009), a higher ratio of mountains will significantly result in bigger values of MCs. In the provinces with higher shares of mountain areas, it will be more costly to conduct the vegetation management to further increase the reliability of electricity supply. The annual maximum temperature also has significant impacts on the MCs. A 1% increase in the peak temperature will increase the MC by an average of 1.060%. This is because the increase of annual maximum temperature will push up the peak load, and the available low-cost measures to reduce power outage lengths become very limited when there is a tight supply-demand constraint (Auffhammer and Mansur, 2014).

4.3. Policy incentives for reducing power outages

Although everyone wants a continuous electricity supply without interruptions, the high reliability comes at a cost. It is necessary to design policies that can provide enough incentives to enhance the reliability of the electricity system. This means that the benefits of reducing power outages should exceed the caused cost if the policy is effective. This section first makes use of the DR compensations and the estimated MCs to judge the incentive effectiveness of the current policies. DR is an important measure proposed by the government to optimize the power system operation from the demand side, and the peak load shifted by DR

Table 4
The comparison between MCs and DSM compensations of 1 h during the peak load period in 2017.

Province	(1) Peak load (GW)	(2) Compensation price (yuan/kWh)	(3)=(1)*(2) Total Compensations (million yuan/h)	(4) Estimated MCs (million yuan/h)	(5)=(3)/(4) Compensations/ MCs	(6) Threshold compensation price (yuan/kWh)
Zhejiang_real time	69.00	4.00	276	455	61%	6.59
Zhejiang_advance	69.00	2.00	138	455	30%	6.59
Jiangshu	98.46	2.83	279	731	38%	7.42
Guangdong	101.93	2.50	255	487	52%	4.78
Shanghai	40.86	2.00	82	551	15%	13.49
Jiangxi	18.41	0.80	15	227	6%	12.33

Notes: the data of compensation price and the peak load are drawn from the provincial Economic and Information Commissions (EICs) and Development and Reform Commissions (DRCs).

can reduce the possibility of power outages. Ten pilot provinces in China have conducted DR since 2014, such as Zhejiang, Jiangsu, Shanghai, etc. Customers, who reduce or postpone their consumption during the peak load period, will receive a certain amount of compensation from the grid companies. Thus, a rational decision-maker of the grid companies will weigh the costs (MCs) and the benefits (reduced payment of DR compensations) in reducing power outages from the supply side. Taken 1 h during peak load period in 2017 as an example, the comparison results of these two choices are shown in Table 4.

As seen from Table 4, the ratios between the total compensations and the estimated MCs range from 6% to 61% in the five pilot provinces. The real-time DR in Zhejiang has the biggest ratio, while the DR in Jiangxi has the smallest ratio. Since all ratios are smaller than 1, the current DR compensations cannot motivate the grid companies to enhance the electricity reliability from the supply side. This is because compensating for the power interruptions is a cheaper choice for them.

Then, the estimated MCs are used to design the compensation prices in the DR mechanism. We first calculate the threshold prices under which the MCs match the total compensations, see the last column in Table 4. The threshold price is the lower bound of prices that grid companies are willing to take actions from the supply side, in order to improve the electricity system reliability. The threshold compensation price in Shanghai ranks first as 13.49 yuan/kWh, while the price in Guangdong is the least as 4.78 yuan/kWh. Therefore, the provincial differences among the compensation prices should be integrated into the designs of DR policies, thus providing effective incentives for different regions.

5. Conclusions and policy implications

5.1. Conclusions

The increasing electrification, climate change, and large scale integration of intermittent renewables have brought challenges for the electricity system reliability in China. Understanding the cost of reducing power outage durations is a prerequisite for designing an optimal reliability enhancement plan. With this motivation, this study has firstly used production theory combined with a parametric distance function approach to estimate the MCs of reducing power interruption lengths in China for the period from 2002 to 2017. Then, we have employed a fixed effects panel data model to investigate the impacts of different environmental factors on the MCs. Finally, the estimated MCs have been used to analyze the incentive effectiveness of current DR policies and to provide suggestions for the price mechanism designs. During this process, we have obtained the following significant conclusions:

(1) The national MCs of reducing 1 h of power outages in China show an increasing trend during the period from 2002 to 2017, ranging from 1.27 billion yuan/hour to 11.63 billion yuan/hour. The MCs vary substantially among different provinces, Jiangsu has the biggest MC (0.73 billion yuan/h) in 2017, while Hainan has the smallest MC (0.07 billion yuan/h). Moreover, the MCs show a negative correlation relationship with the SAIDI values, provinces with higher reliability levels will have higher MCs. Therefore, the provincial heterogeneity regarding the MCs should not only be well integrated into regulation policies of power outages, but also be applied to the improvement plan of electricity system reliability in the future.

(2) The maximum wind speed, annual total number of thunders and lightning, proportions of mountain areas and annual maximum temperature have been identified to have significant positive impacts on the MCs. Moreover, the directions of these impacts are robust when these environmental factors are added to the regression model using a stepwise approach. In order to design more targeted measures to improve the power supply quality, it is crucial for grid companies to establish a dynamic monitoring and tracking mechanism of these factors. In addition, the estimated regression models can also be used to quantify how the MCs will be affected by different reliability improvement measures, thus serving as a useful tool for the cost-benefit analysis.

(3) The total MC of all the provinces is equal to 9.66 billion yuan/hour in 2017, indicating that grid companies only need to spend 6.74% of their annual profits to reduce the current national SAIDI by 1 h. The good affordability leaves much space for the policies to improve the quality of power supply. On the one hand, the estimated MCs can be employed to check the effectiveness of the existing policy designs. Taken the compensation policy in the DR mechanism as an example, the current compensation amounts are only about 6% to 61% of the estimated MCs in the five pilot provinces, which means that grid companies would choose to pay for the compensations rather than to enhance the system reliability from the supply side. Therefore, the compensation standards should be increased to incentivize grid companies to improve the quality of power supply. On the other hand, the least compensation prices for DR policies can be determined based on the estimated MCs in different provinces, such as 4.78 yuan/kWh in Guangdong and 13.49 yuan/kWh in Shanghai.

5.2. Policy implications

Based on the above conclusions, we have proposed the following policy implications to improve electricity reliability as follows.

First, although this study has estimated the MCs of reducing power outage durations in different provinces, an easily accessible platform for publicizing these information is still lacked, thus failing to provide timely and scientific support for the grid companies and policy makers. Therefore, it is good for the government to establish proper platforms to publish and update the MCs of different regions. At the same time, the regulators can also cooperate with the academics to continuously estimate the MCs and to improve the regulatory policies. With the accessible information of power outage cost, grid companies can make wiser choices in the trade-off between different operational targets, while the regulators can also set better-informed quality targets.

Second, the cost of reducing power outage durations has been identified to be affected by the environment where the electricity system works, so the regulation policies of grid companies' performances should be improved or adjusted with consideration of the significant impacts from different environmental factors. This can make the benchmark analysis and performance comparison more fair and operational. Moreover, it is also necessary for the grid companies to track the dynamic changes of their operational environment and then optimize the selection of measures to reduce the power outages, thus enhancing the competiveness in the electricity supply business.

Finally, since the electricity system reliability can be improved from both the supply-side and demand-side, the corresponding policies can also be designed from two sides. The effectiveness of supply side policy will be affected by demand side policies, and vice versa. However, the current interactions and coordination between the two-side policies are not enough, which can be evidenced by the insufficient DR incentives for the supply-side investment. Therefore, it is good for the regulators to design a comprehensive and integrated regulatory framework for the reliability policies, thus reducing the conflicts among different policies.

Although we have answered several questions regarding the MCs of reducing power interruption lengths in China, some places are left to be addressed in future studies. More input and output variables can be used in the cost estimation model to check the robustness of the results when more new data is available. The welfare analysis of electricity reliability changes can also be conducted based on the estimated MCs and customers' willingness to pay for quality improvement. With these work done, more understanding will be achieved regarding the cost of reducing power outage durations.

CRediT authorship contribution statement

Hao Chen: Conceptualization, Methodology, Writing – original draft. **Xi Chen:** Software, Data collection. **Jinye Niu:** Software, Data collection. **Mengyu Xiang:** Data curation, Visualization. **Weijun He:** Methodology. **Sinan Küfeoğlu:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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