An optimization scheme for designing power rationing schedules in a long-term power shortage

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ABSTRACT

Power rationing is the last resort to prevent large-scale blackouts after demand response resources are exhausted during power shortages. However, the traditional rolling blackout method has been criticized for causing significant losses. To address this issue, this paper proposes a novel optimization scheme for designing power rationing schedules in a long-term power shortage, which considers different types of consumers at multiple time scales. The proposed scheme takes into account economic losses due to limited power supply, disruptions in industrial chains, and the social costs caused by excessive activation of the same consumers. First, consumers are categorized as maintenance consumers, work-shift consumers, and fast-response consumers based on their consumption characteristics. Then, a two-stage stochastic programming model is presented to account for long-term uncertainties in power shortage, which yields the maintenance and work-shifting schedules. Given these predetermined schedules, once the demand-supply gap is better revealed in real-time, a dispatch model for fast-response consumers is solved to generate the activation schedules. The case study demonstrates that the proposed scheme can effectively reduce costs when compared to the rolling blackout approach, as well as respecting industrial chain coupling and fairness.

1. Introduction

The penetration of renewable energy sources has dramatically increased in recent years, and extreme weather events occur more frequently worldwide, leading to power shortages in some countries. For example, in 2019, South Africa was severely affected by floods and harsh weather conditions, leading to the implementation of rolling blackouts that lasted for 2 to 4 hours at a time [1]. Similarly, in February 2021, the ERCOT power grid experienced blackouts for several days due to the winter storm Uri [2]. In July and August of 2022, several provinces in China had to implement orderly power usage[1] during heat waves [3, 4].

Unfortunately, power rationing has become a recurring problem in certain countries, such as Brazil [5], Pakistan [6] and Nepal [7]. It often lasts for consecutive days, particularly during long-term power shortages caused by extreme weather conditions such as cold or heat waves and dark doldrums. This can result in significant economic and social losses. To address this issue, it is necessary to increase the system adequacy by investing in new generation capacity in the long run. However, in the short term,it is crucial to optimize the utilization of the existing infrastructure by implementing more efficient consumer rationing strategies during periods of shortages. Despite the significance of this topic, the prevailing method for implementing power rationing is through simple rolling blackouts, wherein distribution feeders are disconnected in a sequential manner for a predetermined duration, resulting in an overall reduction of the total load. Nevertheless, the rolling blackout method has been criticized for causing significant losses because it does not discriminate between higher-cost and lower-cost loads. Consumers often exhibit distinct consumption characteristics, and there is a limited amount of research available on optimizing power rationing schedules accounting for different consumer types at multiple time scales. Consequently, the research question attempted in this paper is how to design an optimization scheme specifically for this purpose, in order to mitigate the adverse impacts of power rationing on both the economy and society in a long-term shortage. More specially, the following issues need to be addressed when designing power rationing schedules in a long-term power storage.

(i) Consumers have different consumption characteristics and could be rationed at various time scales, especially those in the industrial sector. For example, some plants have a yearly or monthly maintenance plan, which would

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[1] It is similar to rolling blackouts, but in a more organized way.

be ideal if scheduled in power shortage periods. Some others are flexible to shift workdays and non-workdays in the week. Another type is able to response within half an hour and could be rationed on short notice. It is an open question how to coordinate these consumers at minimal costs in case of long-term shortages.

(ii) It is undesirable to ration the same consumers repeatedly for the sake of social stability and public opinion. Instead, fairness and historical contributions should be taken into consideration.

(iii) Post-pandemic economic recovery is the focus of most countries now and inappropriate power rationing can disrupt industrial chains, resulting in significant economic losses. Thus, it is crucial to account for industrial chain coupling when power rationing is implemented, as it can have a cascading effect on downstream businesses. Taking the integrated circuits industry as an example, if fabs stopped operating, the downstream packaging and testing companies would suffer from increased costs, prolonged delivery of products or even downtime.

This paper aims to tackle these challenges, and make contributions in the following three aspects.

(i) An optimization scheme based on stochastic programming is introduced to coordinate consumers across multiple time scales, which can effectively handle uncertainties in long-term shortages. The stochastic model outperforms the deterministic model in 79 out of 100 scenarios and reduces the average total costs by 2.96%.

(ii) Impact factors are proposed, in order to represent industrial chain coupling and reduce disruptions to the entire chain. The synchronized rationing of consumers within the same industrial chain significantly reduces total costs by 19.8%∼193.5% with an average of around 51.8%.

(iii) Fairness factors are adopted, in order to account for a consumer's historical contributions and level of cooperation with the system operator. It mitigates excessive activation of the same fast-response consumer by 30.1%∼35.2% in terms of average number of activations.

The remaining sections of this paper are organized as follows. Section 2 reviews related work. Section 3 describes the two-stage stochastic model that generates maintenance and work-shift schedules, and a real-time activation model for fast-response consumers. Section 4 provides a case study to demonstrate the effectiveness of the proposed model. Finally, section 5 draws conclusions, discusses practical implementation aspects and limitations of this proposal, and points out directions for future research.

2. Literature review

There has been a growing interest in developing alternative power rationing schemes to replace conventional rolling blackouts. One such scheme [8] introduces a transactive rationing mechanism inspired by quota-based systems. This mechanism ensures a minimum level of service for all customers and employs market-based control to prioritize critical loads. The effectiveness of this mechanism is verified at both the feeder and microgrid levels. Additionally, a stochastic optimal robust design presented in [9] addresses multi-stage under-frequency load shedding, which accounts for load priorities to shed the minimum optimal load. Furthermore, an under-voltage load shedding approach based on particle swarm optimization and artificial neural networks is introduced in [10], which optimizes load shedding plans and costs. However, these studies primarily focus on real-time or short-term power shortages at the feeder or microgrid level, whereas this paper addresses a long-term power shortage at the system level.

In addition to the aforementioned studies, there is a separate body of research focusing on power rationing at a broader scale. For instance, a study [11] presents an efficient regional rationing approach specifically designed for the Netherlands, where municipalities with lower costs are prioritized for rationing to minimize welfare losses. The trade-off between rationing quantity and fairness is explored for Nigeria by evaluating the consequences of deviating from proportional allocation targets for various regions during long-term shortages [12]. While these works ration consumers on a regional basis, this study aims to send specific curtailment signals directly to individual consumers.

Another relevant topic is "energy-efficient production planning", which primarily focuses on enhancing energy efficiency and reducing energy costs within manufacturing plants. In the study cited as [13], the emphasis lies on energy-aware flexible shop scheduling environments. To achieve hierarchical optimization across multiple objectives such as energy-related factors (total energy) and temporal factors (makespan, total flow time, and total idle time), a decision support system comprising an iterated local search algorithm is proposed. Furthermore, a nonlinear mixed-integer optimization model is introduced in [14], which evaluates the trade-off between electricity costs and electricity consumption under real-time pricing and time-of-use pricing. In [15], a mixed-integer linear programming model is formulated considering a distinct electricity tariff structure comprising an energy charge and a demand charge, with the aim of minimizing the total electricity cost. While the aforementioned works primarily address short-term production planning problems, the model presented in [16] takes into account both short-term and long-term flow shop scheduling problems. This model aims to minimize energy costs by considering time-varying electricity prices derived from the day-ahead market EPEX Spot Germany/Austria, as well as future price scenarios spanning days or weeks ahead. In [17, 18], grid-connected generation systems are taken into account, and a mixed-integer linear programming approach is adopted to model the energy-aware scheduling problem in manufacturing plants. For a more comprehensive review on this topic, readers are encouraged to refer to [19, 20, 21]. In order to further enhance process efficiency, researchers have suggested that optimizing production planning should be integrated with scheduling maintenance tasks [22, 23], especially for preventive maintenance, which involves regular maintenance activities to proactively prevent unexpected failures. In this context, the authors of [24] introduce the concept of "Stable Maintenance Task Scheduling", to account for system robustness and stability. They propose a bi-objective robust optimization model to achieve this goal. While optimization methods have been widely employed for addressing maintenance tasks scheduling challenges [25], reinforcement learning techniques are gaining more attention [26, 27], due to their great potential in generating maintenance policies that surpass most conventional strategies. Notably, the advent of Industry 4.0 and the Internet of Things has paved the way for new trends in maintenance task scheduling. For an in-depth exploration of these emerging trends, interested readers can delve into the comprehensive reviews provided in [28, 29]. However, this paper stands apart from the existing body of work due to its unique focus on optimizing the rationing scheduling of consumers from the perspective of the power system operator, in order to meet the power demand-supply gap. In contrast, theses previous studies concentrate on scheduling the production and maintenance activities of specific manufacturing plants to achieve their individual targets.

Despite these advancements, the identified research gaps have not been addressed when designing power rationing schedules in a long-term power storage. This paper proposes an optimization scheme for this purpose, encompassing a two-stage stochastic model to generate maintenance and work-shift schedules, and an activation model for fast-response consumers based on real-time demand-supply gaps.

3. Model

3.1. Problem description

During extreme weather events, such as hot and cold waves, power shortages could last for several weeks. Typically, shortages occur during morning and evening peak hours, which may require power rationing to prevent blackouts. This paper focuses on industrial and commercial consumers, who can be classified into three categories based on their power consumption characteristics.

- Maintenance consumers, who have a relatively stable consumption profile over the year but schedule a maintenance for production lines once per year, e.g., chemical industry and steel industry. Therefore, it is preferable that the maintenance is scheduled during power shortage periods.
- Work-shift consumers, who typically consume power five days per week on the weekdays, but are able to shift their workdays to other days in the week.
- Fast-response consumers, who are able to decrease their power consumption to a specified level with half an hour, e.g., machinery & equipment industry.

Maintenance and work-shift consumers differ from fast-response consumers because their power rationing schedules need to be determined in advance so that they can plan their maintenance or work-shift activities. However, predicting power demand-supply gaps accurately in the long term is challenging. Therefore, a two-stage stochastic programming model is proposed, as shown in the upper panel of Figure 1. Stochastic approaches, such as stochastic optimization [30], stochastic control [31], and stochastic analysis [32], have been widely adopted to tackle uncertainties in various domains. In this paper, the proposed optimization scheme is centered around this two-stage stochastic programming model. Apart from stochastic optimization, robust optimization and chance-constrained optimization are also commonly used methods in the field of optimization under uncertainty [33]. Given that the proposed power rationing scheme aims to minimize expected costs and assuming there are sufficient consumers that can be rationed,

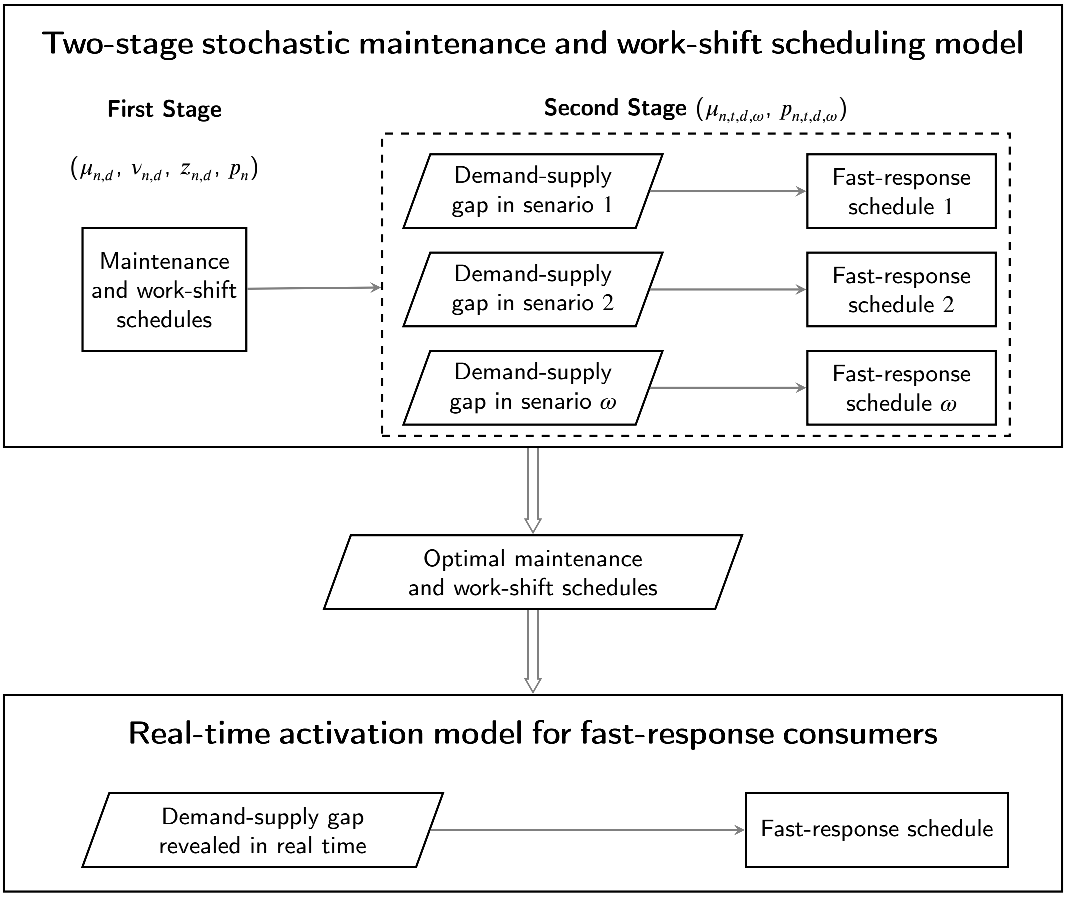


Figure 1: Representation of the proposed scheme to optimize power rationing schedules, which consists of the two-stage stochastic maintenance and work-shift scheduling model, and the real-time activation model for fast-response consumers. The former generates power rationing schedules for maintenance and work-shift consumers, designated as maintenance and work-shift schedules. On the other hand, the latter produces power rationing schedules tailored to fast-response consumers, known as fast-response schedules. Industrial chains are considered across the models.

which guarantees the feasibility of the model, stochastic optimization is employed as the chosen modeling approach. The overall objective of this model is to minimize the expected total costs, including economic losses and social costs of fairness. In the first stage, maintenance and work-shift schedules are generated, while the second stage determines how to activate fast-response consumers in each scenario of demand-supply gaps. After solving the two-stage stochastic model, the maintenance and work-shift schedules are subsequently input into a real-time activation model, as depicted in the lower panel of Figure 1. When the demand-supply gap is better revealed (based on short-term forecasts, for example), this model is solved to yield a schedule for fast-response consumers. Appendix A summarizes the notations introduced in the subsequent detailed mathematical formulations.

3.2. Problem formulation

In this section, we present the mathematical formulation of the two-stage stochastic maintenance and work-shift scheduling model, and the real-time activation model for fast-response consumers.

3.2.1. A two-stage stochastic maintenance and work-shift scheduling model

This section introduces the two-stage stochastic programming model used to generate maintenance and work-shift schedules. The model aims to minimize the expected total costs over multiple scenarios while respecting constraints related to the power consumption characteristics of different types of consumers.

To minimize economic losses, power rationing schedules are announced beforehand to maintenance and work-shift consumers, allowing them to adjust their production plans accordingly. This approach ensures that the costs of rationing these consumers are negligible. However, if upstream consumers in the same industrial chain of a maintenance or work-shift consumer n are also undergoing maintenance or shift work, then consumer n may suffer economic losses. The total cost of rationing maintenance and work-shift consumers can be calculated using Equation (1).

$$f^{\mathrm{MS}} = \sum_{\substack{n \in \mathcal{N}^{\mathrm{MS}} \\ d \in \mathcal{D}}} \frac{\sum\limits_{n' \in \mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'} \cdot \mu_{n',d}}{\sum\limits_{n' \in \mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'}} \cdot \alpha_n \cdot C_n \cdot (1 - \mu_{n,d}) \cdot P_n, \tag{1}$$

where $n \in \mathcal{N}^{\mathrm{MS}}$ represents maintenance or work-shift consumers; $d \in \mathcal{D}$ represents the day of power rationing; $\mu_{n,d}$ is binary decision that indicates whether consumer n is subject to power rationing on day d; α_n is a parameter that reflects the impact of upstream consumers on n; C_n is the cost of rationing consumer n. The set $\mathcal{N}^{\mathrm{MS}}$ includes all maintenance and work-shift consumers, while $\mathcal{N}_n^{\mathrm{Up,MS}}$ refers to the set of maintenance and work-shift consumers upstream of consumer n in the same industrial chain. This equation encompasses the following cases.

- If a maintenance or work-shift consumer $n \in \mathcal{N}^{\mathrm{MS}}$ is rationed, no costs are incurred since the consumer is prepared for the rationing. In other words, $\mu_{n,d} = 1$ yields $1 - \mu_{n,d} = 0$, resulting in $f^{\mathrm{MS}} = 0$.
- If consumer $n \in \mathcal{N}^{\mathrm{MS}}$ is not rationed (i.e., $\mu_{n,d} = 0$),
  - if its upstream consumers are not rationed either, then there are no economic losses. In Equation (1), $\mu_{n',d} = 0, \forall n' \in \mathcal{N}_n^{\mathrm{Up,MS}}$, yields $f^{\mathrm{MS}} = 0$.
  - if the upstream consumers are rationed, the industrial chain may be disrupted, causing n to suffer economic losses due to increased inventory costs or a lack of raw materials. The extent of the disruption can be represented by the fraction of curtailed power of upstream consumers, i.e, $\sum_{n' \in \mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'} \cdot \mu_{n',d} / \sum_{n' \in \mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'}$. Taking into consideration of the impact factor α_n, Equation (1) is formulated.

In contrast to maintenance and works-shift consumers, fast-response consumers are activated with short notice, and any interruption to their production plans could have a significant economic impact. Besides economic losses, there are also social costs associated with fast-response consumers. These consumers prefer a fair activation, as activating the same consumers every day during a two-week power shortage would be unfair and likely lead to complaints. Furthermore, even if a fast-response consumer n is not rationed, the propagation of industrial chain disruptions due to maintenance and work-shift schedules could still affect it. Taking these factors into consideration, the total expected costs of fast-response consumers is expressed as:

$$\begin{aligned} f^{\mathrm{F}} = \sum_{\omega \in \Omega} \mathrm{Pr}_{\omega} \cdot \sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} \sum_{n \in \mathcal{N}^{\mathrm{F}}} \Bigg[& C_n \cdot p_{n,t,d,\omega} \cdot (1 + \beta_n \cdot \sum_{d'=1}^{d-1} \sum_{\tau \in \mathcal{T}} \mu_{n,\tau,d,\omega}) + \\ & \frac{\sum_{n' \in \mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'} \cdot \mu_{n',d}}{\sum_{n' \in \mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'}} \cdot \alpha_n \cdot C_n \cdot (1 - \mu_{n,t,d,\omega}) \cdot \overline{P}_{n,t} \Bigg] \end{aligned} \tag{2}$$

where C_n represents the economic cost of rationing consumer $n \in \mathcal{N}^{\mathrm{F}}$, while $p_{n,t,d,\omega}$ is the curtailed power in period t day d scenario ω and $\mu_{n,t,d,\omega}$ denotes whether consumer n is activated in period t day d scenario ω. $\overline{P}_{n,t}$ represents the upper bound of the curtailable power of consumer n. In addition, some consumers view power curtailment as a social responsibility when the system is stressed and wish to contribute. Therefore, to accommodate the preferences of different fast-response consumers, a fairness factor denoted by β_n is introduced. This equation covers the following cases.

- If a fast-response consumer $n \in \mathcal{N}^{\mathrm{F}}$ is rationed (i.e., $\mu_{n,t,d,\omega} = 1$), the second term of in the brackets of Equation (2) equals zero. Regarding the first term $C_n \cdot p_{n,t,d,\omega} \cdot (1 + \beta_n \cdot \sum_{d'=1}^{d-1} \sum_{\tau \in \mathcal{T}} \mu_{n,\tau,d,\omega})$,

- if consumer n is cooperative and indifferent to fairness, the $\beta_n = 0$ and rationing costs only include economic losses, calculated as $C_n \cdot p_{n,t,d,\omega}$.
- if consumer n is concerned about fairness, the number of activation from the first day until day d is represented by $\sum_{d'=1}^{d-1} \sum_{\tau \in \mathcal{T}} \mu_{n,\tau,d,\omega}$. Thus the rationing costs of consumer n accounts for accumulated activation and the fairness factor β_n.

- Even if a fast-response consumer $n \in \mathcal{N}^{\mathrm{F}}$ is not rationed (i.e., $\mu_{n,t,d,\omega} = 0$ and $p_{n,t,d,\omega} = 0$ as required by Equation (20)) , the propagation of industrial chain disruptions due to maintenance and work-shift schedules could still affect it. The first term of in the brackets of Equation (2) equals zero. Regarding the second term $\sum_{n' \in \mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'} \cdot \mu_{n',d} / \sum_{n' \in \mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'} \cdot \alpha_n \cdot C_n \cdot (1 - \mu_{n,t,d,\omega}) \cdot \overline{P}_{n,t}$,
  - if its upstream consumers are not rationed either, then there are no economic losses and $f^{\mathrm{F}} = 0$.
  - if the upstream consumers are rationed, the economic loss is proportional to the fraction of curtailed power of upstream consumers, multiplied by the impact factor α_n.

Summing up Equation (1) and Equation (2) to derive the overall objective function, and integrating constraints defined by equations (4)∼(21), the two-stage stochastic programming model is obtained as follows.

$$\min\ f = f^{\mathrm{MS}} + f^{\mathrm{F}} \tag{3}$$

$$\text{s.t.} \sum_{n \in \mathcal{N}^{\mathrm{MS}}} p_{n,d} + \sum_{n \in \mathcal{N}^{\mathrm{F}}} p_{n,t,d,\omega} \geq L_{t,d,\omega}, \forall t, \forall d, \forall \omega, \tag{4}$$

$$p_{n,d} = P_n \cdot \mu_{n,d}, \forall n \in \mathcal{N}^{\mathrm{M}}, \forall d \tag{5}$$

$$\sum\nolimits_{d \in \mathcal{D}} \mu_{n,d} = D_n^{\mathrm{M}}, \forall n \in \mathcal{N}^{\mathrm{M}} \tag{6}$$

$$\sum\nolimits_{d'=d-D_n^{\mathrm{M}}+1}^{d} v_{n,d'} \leq \mu_{n,d}, \forall n \in \mathcal{N}^{\mathrm{M}}, d \geq D_n^{\mathrm{M}} \tag{7}$$

$$\sum\nolimits_{d \in \mathcal{D}} v_{n,d} = 1, \forall n \in \mathcal{N}^{\mathrm{M}} \tag{8}$$

$$\sum\nolimits_{d \in \mathcal{D}} z_{n,d} = 1, \forall n \in \mathcal{N}^{\mathrm{M}} \tag{9}$$

$$\mu_{n,d} \leq v_{n,d}, \forall n \in \mathcal{N}^{\mathrm{M}}, d = 1 \tag{10}$$

$$\mu_{n,d} = \mu_{n,d-1} + v_{n,d} - z_{n,d}, \forall n \in \mathcal{N}^{\mathrm{M}}, \forall d \geq 2 \tag{11}$$

$$\mu_{n,d}, v_{n,d}, z_{n,d} \in \{0, 1\}, \forall n \in \mathcal{N}^{\mathrm{M}}, \forall d \tag{12}$$

$$p_{n,d} = P_n \cdot \mu_{n,d}, \forall n \in \mathcal{N}^{\mathrm{S}}, \forall d \tag{13}$$

$$\mu_{n,d} = \mu_{n,d+7}, \forall n \in \mathcal{N}^{\mathrm{S}}, d \leq D - 7 \tag{14}$$

$$\sum\nolimits_{d'=d-6}^{d} \mu_{n,d'} = D_n^{\mathrm{S}}, \forall n \in \mathcal{N}^{\mathrm{S}}, d \geq 7 \tag{15}$$

$$\sum\nolimits_{d'=d-D_n^{\mathrm{S}}+1}^{d} v_{n,d'} \leq \mu_{n,d}, \forall n \in \mathcal{N}^{\mathrm{S}}, d \geq D_n^{\mathrm{S}} \tag{16}$$

$$\mu_{n,d} \leq v_{n,d}, \forall n \in \mathcal{N}^{\mathrm{S}}, d = 1 \tag{17}$$

$$\mu_{n,d} = \mu_{n,d-1} + v_{n,d} - z_{n,d}, \forall n \in \mathcal{N}^{\mathrm{S}}, d \geq 2 \tag{18}$$

$$\mu_{n,d}, v_{n,d}, z_{n,d} \in \{0, 1\}, \forall n \in \mathcal{N}^{\mathrm{S}}, \forall d \tag{19}$$

$$\underline{P}_{n,t} \cdot \mu_{n,t,d,\omega} \leq p_{n,t,d,\omega} \leq \overline{P}_{n,t} \cdot \mu_{n,t,d,\omega} \tag{20}$$

$$\sum_{t \in \mathcal{T}} \mu_{n,t,d,\omega} \leq 1, \forall n \in \mathcal{N}^{\mathrm{F}}, \forall d \in \mathcal{D}, \forall \omega \in \Omega \tag{21}$$

The total curtailed power from rationed maintenance and work-shift consumers $\sum_{n \in \mathcal{N}^{\mathrm{MS}}} p_{n,d}$, and fast-response consumers $\sum_{n \in \mathcal{N}^{\mathrm{F}}} p_{n,t,d,\omega}$ should satisfy the demand-supply gap, as indicated by Equation (4), where $L_{t,d,\omega}$ is the gap in period $t \in \mathcal{T}$ day $d \in \mathcal{D}$ scenario $\omega \in \Omega$.

When a maintenance consumer n is subject to power rationing, their curtailed power equals the maximum power that can be curtailed; otherwise, their curtailed power is zero indicated by Equation (5). If a maintenance consumer n begins maintenance, they remain in this state for D_n^{M} consecutive days, as specified by Equations (6) and (7). Additionally, each maintenance consumer only conducts maintenance once during the power shortage horizon. To account for the complex dynamics of a maintenance consumer, three sets of binary variables are introduced: $\nu_{n,d}$, $\mu_{n,d}$ and $z_{n,d}$. These variables are inspired by unit commitment models and are defined in Equations (8)-(11)[2], where $\nu_{n,d}$ denotes whether consumer n starts maintenance on day d, while $z_{n,d}$ denotes whether consumer n finishes maintenance on day d.

The model also involves work-shift consumers who, similar to maintenance consumers, have a curtailed power that is limited to the maximum curtailable power when in a state of power rationing, as shown in Equation (13). Work-shift consumers operate on a weekly cycle, as described by Equation (14), where each consumer has D_n^{S} consecutive non-workdays per week, as required by Equations (15)-(16). The state transition dynamics are described by Equations (17)-(18).

In contrast, fast-response consumer n has a curtailed power that is bounded by both the maximum and minimum curtailable power $\overline{P}_{n,t}$ and $\underline{P}_{n,t}$ if activated, as required by Equation (20). Each consumer is activated only once per day, despite potential shortages during both morning and evening peak hours, expressed by Equation (21).

3.2.2. Real-time activation model for fast-response consumers

In section 3.2.1, a two-stage stochastic programming model was presented that generates maintenance and work-shift schedules, taking into account various demand-supply gap scenarios. The model produces these schedules in advance. Once the schedules are in place, and since historical data on fast-response consumer activation is available, the following optimization model is used to generate real-time activation plans for fast-response consumers. This optimization model is executed when the actual supply-demand gap $L_{\tilde{t},\tilde{d}}$ (or its short-term forecast) for period $\tilde{t}$ day $\tilde{d}$ is revealed.

$$\min\ f(\tilde{t},\tilde{d}) = \sum_{n\in\mathcal{N}^{\mathrm{F}}}\left[C_n\cdot p_{n,\tilde{t},\tilde{d}}\cdot(1+\beta_n\cdot\sum_{d'=1}^{\tilde{d}-1}\sum_{\tau\in\mathcal{T}}\mu^*_{n,\tau,d}) + \frac{\sum_{n'\in\mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'}\cdot\mu^*_{n',d}}{\sum_{n'\in\mathcal{N}_n^{\mathrm{Up,MS}}} P_{n'}}\cdot\alpha_n\cdot C_n\cdot(1-\mu_{n,\tilde{t},\tilde{d}})\cdot\overline{P}_{n,\tilde{t}}\right]$$

$$\text{s.t.}\ \sum_{n\in\mathcal{N}^{\mathrm{MS}}} p^*_{n,\tilde{d}} + \sum_{n\in\mathcal{N}^{\mathrm{F}}} p_{n,\tilde{t},\tilde{d},\omega} \geq L_{\tilde{t},\tilde{d}} \tag{22}$$

$$\underline{P}_{n,\tilde{t}}\cdot\mu_{n,\tilde{t},\tilde{d}} \leq p_{n,\tilde{t},\tilde{d}} \leq \overline{P}_{n,t}\cdot\mu_{n,\tilde{t},\tilde{d}}, n\in\mathcal{N}^{\mathrm{F}} \tag{23}$$

$$\sum_{\tau=1}^{\tilde{t}}\mu_{n,\tau,\tilde{d}} \leq 1, \forall n\in\mathcal{N}^{\mathrm{F}} \tag{24}$$

The symbol * is used to represent the optimal solutions, which include both the maintenance and work-shift schedules $\mu^*_{n',d}$ from the stochastic model presented in section 3.2.1, and the historical activation of fast-response consumers $\mu^*_{n,\tau,d}$, which are treated as parameters. The objective function aims to minimize the total cost of rationing fast-response consumers during period $\tilde{t}$ on day $\tilde{d}$. Curtailed power from all consumers satisfies the demand-supply gap $L_{\tilde{t},\tilde{d}}$ through constraint (22). Additionally, constraint (23) imposes lower and upper bounds on the curtailed power of each n, while constraint (24) limits each fast-response consumer to only one activation per day. The model is solvable by off-the-shelf solvers.

3.3. Problem reformulation and solution

Even though the real-time activation model in section 3.2.2 is solvable by off-the-shelf solvers, the two-stage stochastic programming model in section 3.2.1 involves the product of a binary decision variable and a continuous decision variable, resulting in a bi-linear term $p_{n,t,d,\omega}\cdot\mu_{n,\tau,d,\omega}$ in Equation (2). To overcome this challenge, it is equivalently expressed using the McCormick envelope [34]. Since $p_{n,t,d,\omega}$ is bounded within $0 \leq p_{n,t,d,\omega} \leq \overline{P}_{n,t}$, a new variable $y_{n,t,\tau,d,\omega}$ is introduced, to represent $p_{n,t,d,\omega}\cdot\mu_{n,\tau,d,\omega}$. Then impose constraints (25)-(28) to substitute $p_{n,t,d,\omega}\cdot\mu_{n,\tau,d,\omega}$ with $y_{n,t,\tau,d,\omega}$, thus reformulating the model as a mixed-integer linear program, which can be solved using off-the-shelf solvers.

$$y_{n,t,\tau,d,\omega} \geq 0 \tag{25}$$

[2]The similarity between maintenance consumers and unit commitment lies in the fact that maintenance consumers, similar to the start-up of a unit, are scheduled to begin maintenance on a specific day. However, there is a notable difference in that maintenance consumers remain in the maintenance state for a fixed number of days and only undergo maintenance once during the entire power rationing horizon. This distinction sets them apart from units, which may undergo multiple start-up and shut-down transitions throughout the specified time period.

Table 1
Overview of numerical simulations conducted in the study.

Simulation	Motivation	Section
Performance of the proposed model	Comparison of the two-stage stochastic programming model to a deterministic model, and the rolling blackout method in terms of total costs.	4.2
Impacts of industrial chains	Comparison of power rationing costs and schedules in the cases of considering / neglecting industrial chain coupling, and providing insights.	4.3
Impacts of fairness	Comparison of power rationing schedules for fast-response consumers in the cases of considering / neglecting fairness, and providing insights.	4.4
Sensitivity on consumer categories	What if more consumers are categorized as fast-response consumers?	4.5

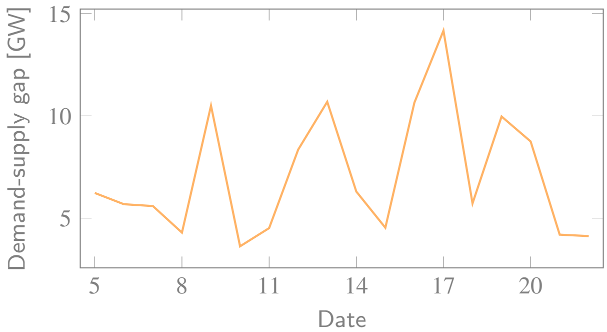


Figure 2: Demand-supply gap of a province in East China in October 2021.

$$y_{n,t,\tau,d,\omega} \leq p_{n,t,d,\omega} \tag{26}$$

$$y_{n,t,\tau,d,\omega} \leq \overline{P}_{n,t} \cdot \mu_{n,\tau,d,\omega} \tag{27}$$

$$y_{n,t,\tau,d,\omega} \geq \overline{P}_{n,t} \cdot \mu_{n,\tau,d,\omega} + p_{n,t,d,\omega} - \overline{P}_{n,t} \tag{28}$$

4. Results

In order to validate the proposed scheme and offer insights into its functionality, a set of numerical simulations is conducted in the study, an overview of which is presented in Table 1.

4.1. System settings

Numerical simulations are conducted based on the historical data of a province in East China, presented in Figure 2. The peak demand in 2021 for this province was approximately 125GW and power shortage lasted 18 consecutive days in October. However, long-term demand-supply gaps are difficult to forecast accurately due to various sources of uncertainties, such as renewable production and cold or heat waves. Instead of modeling every source of uncertainty in a detailed manner, which would be complex and challenging, these uncertainties are incorporated as scenarios of demand-supply gaps. Multiple scenarios are generated using the data presented in Figure 2, following the procedures outlined below:

(i) Based on historical data, the probability of demand-supply gaps lying in the intervals of 3.6~6.3 GW, 6.3~10.7GW and 10.7~14.2 GW was determined to be 11/18, 1/3 and 1/18, respectively. To simulate a consecutive power shortage of two weeks, 130 scenarios are generated following a uniform distribution, with each scenario consisting of 14 values.

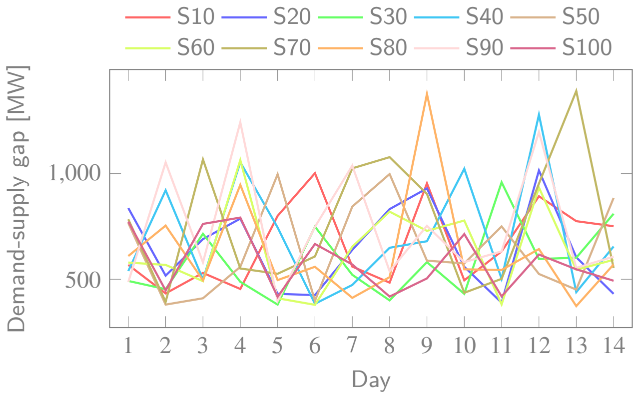


Figure 3: Prefecture-level demand-supply gap scenarios based on the data of a province in East China in October 2021.

Table 2
Parameters of maintenance consumers.

ID	Curtailable power [MW]	Cost [¥/day/kW]	Maintenance duration [Day]	α	Industrial chain	Upstream consumers
M1	100	20	3	0	C1	
M2	90	19	4	0	C1	
M3	80	18	3	0.5	C1	M1, M2
M4	70	17	7	0		
M5	60	16	3	0		
M6	100	15	3	0		
M7	100	15	3	0		
M8	90	15	3	0.2	C1	M1, M2
M9	90	15	3	0.2	C1	M1, M2

(ii) The demand-supply gaps are scaled down by a factor of 10 in order to represent the prefecture-level gaps because power rationing is not implemented at the provincial level but at the prefecture level, owing to network and administrative reasons.

Figure 3 shows a subset of the generated scenarios, highlighting the significant uncertainties involved in future demand-supply gaps. 30 out of the 130 scenarios were used to solve the two-stage stochastic maintenance and work-shift scheduling model, which yielded maintenance and work-shift schedules. The other 100 scenarios were used to simulate the revealed gap in real-time and solve the real-time activation model for fast-response consumers. It is assumed there exists three industrial chains, with each consumer's parameters given in Tables 2 to 4. The model is implemented in Python / Pyomo using PyCharm as the IDE and solved using Gurobi 9.5 on a laptop equipped with an Intel Core i7-1165G7 CPU and 32GB of RAM. The two-stage stochastic programming model can be solved with a MIP gap of 0.1 %, within a ten-minute timeframe.

4.2. Performance of the two-stage stochastic programming model

Stochastic programming is an effective method for dealing with uncertainties. To evaluate its performance, a comparison is made between a two-stage stochastic model and a deterministic model. The deterministic model uses a fixed forecast of the demand-supply gap to schedule maintenance and work-shift consumers, assumed to be 665 MW, which is the average of scenarios adopted in the stochastic model. In addition, the results are compared to the rolling blackout method.

Both the Stochastic and deterministic models are first solved to obtain maintenance and work-shift schedules, and the real-time activation model for fast-response consumers is then solved under 100 scenarios. The resulting total costs (including maintenance, work-shift, and activating fast-response consumers) are compared in Figure 4. Since the demand-supply gaps in different scenarios vary significantly, the 25th percentile to 75th percentile range is wide.

Table 3
Parameters of work-shift consumers.

ID	Curtailable power [MW]	Cost [¥/day/kW]	Maintenance duration [Day]	α	Industrial chain	Upstream consumers
S1	60	16	2	0	C2	
S2	60	16	2	0	C2	
S3	70	17	2	0	C2	
S4	80	15	2	0		
S5	100	20	2	0.5	C1	M3
S6	110	21	2	0	C3	
S7	120	22	2	0	C3	
S8	130	23	2	0	C2	
S9	140	24	2	0.5	C2	S1-3

Table 4
Parameters of fast-response consumers.

ID	Max curtailable power [MW]	Min curtailable power[MW]	Cost [¥/kWh]	α	β	Industrial chain	Upstream consumers
F1	150	15	4	0	0.3		
F2	150	0	4	0	0		
F3	150	0	10	0	0		
F4	150	15	9	0	0.1		
F5	150	0	9	0.25	0	C3	S6-8
F6	150	0	9	0.3	0	C3	S6-8
F7	200	0	25	0	0		

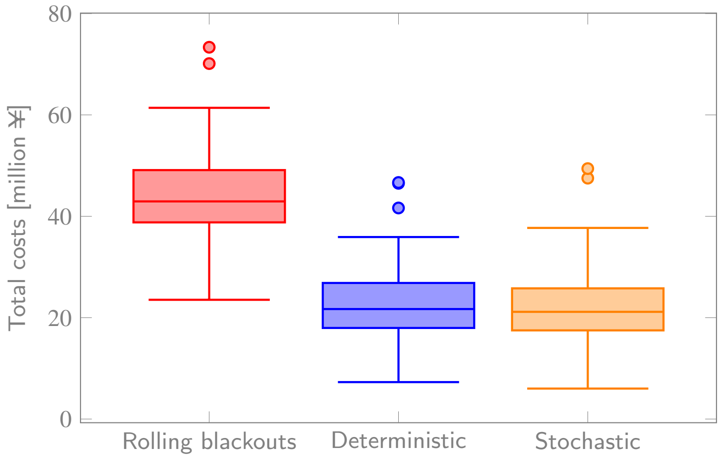
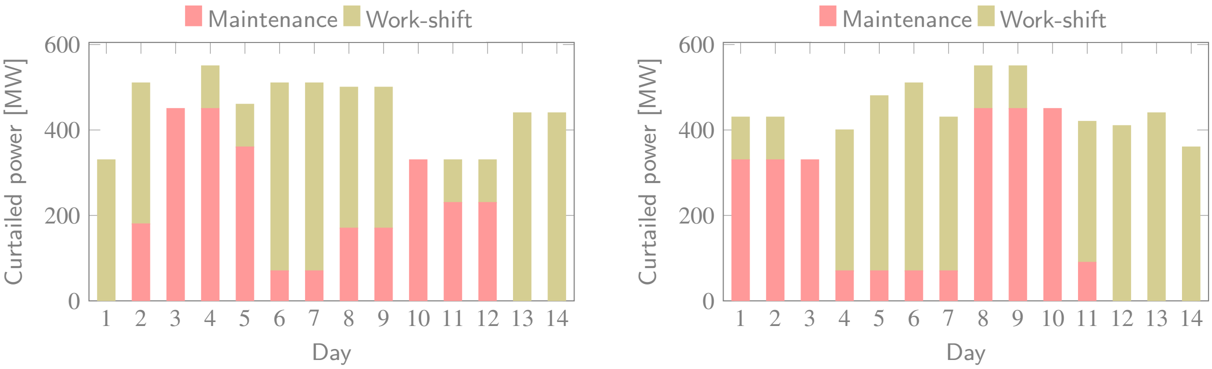


Figure 4: Boxplots of total power rationing costs in 100 scenarios for the rolling blackout method, deterministic scheme and stochastic scheme.

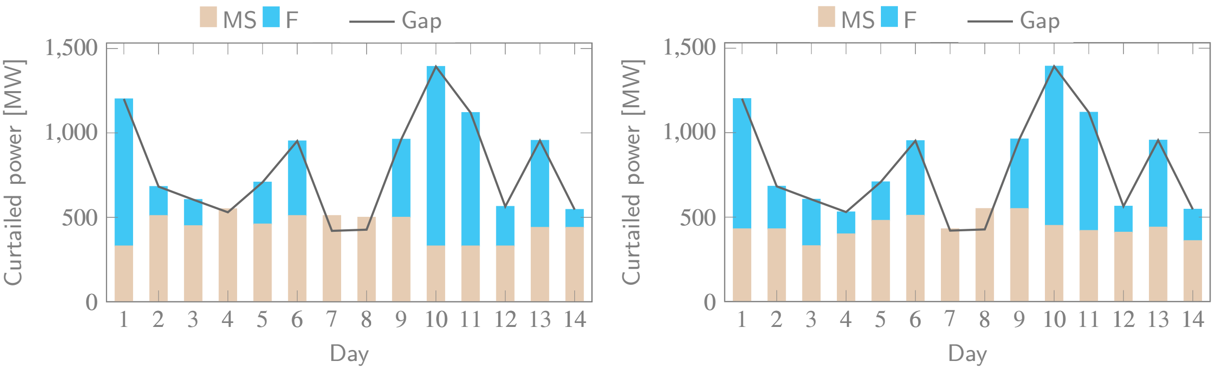
Nevertheless, the rolling blackout method leads to substantial costs as it fails to differentiate between consumers with high costs and those with low costs. The average total cost in the deterministic scheme is 22.41 million ¥, which is 2.96% higher than that in the stochastic scheme. In addition, the stochastic model outperforms the deterministic one in 79 out of 100 scenarios.

The cost difference between the deterministic and stochastic schemes is due to the difference in maintenance and work-shift schedules, which affects the activation of fast-response consumers. As shown in Figure 5, the daily curtailed



(a) Deterministic (b) Stochastic

Figure 5: Maintenance and work-shift schedules from the deterministic scheme (a) and stochastic scheme (b) in scenario 104.



(a) Deterministic (b) Stochastic

Figure 6: Power rationing schedules from the deterministic model (a) and stochastic model (b). MS: power curtailment form maintenance and work-shift consumers; F: power curtailment from fast-response consumers; Gap: demand-supply gap.

power from maintenance and work-shift consumers fluctuates more in the deterministic scheme. This could lead to higher total costs if the actual demand-supply gap differs remarkably from the forecast. For instance, the curtailed power from maintenance and work-shift consumers is relatively lower on day 1 and 10∼12, but if serious power shortage occurred on these days, a large amount of power curtailment would be imposed on fast-response consumers, which leads to significant costs. In contrast, the curtailed power from maintenance and work-shift consumers is more evenly distributed in the stochastic scheme, which would effectively reduce the possibility of such situations.

Scenario 104 further elaborates the advantages of the stochastic scheme. The total costs of the stochastic scheme are 9.4% lower than those of the deterministic scheme. The cost savings are mainly due to the following reasons. As shown in Figure 6, the curtailed power from maintenance and work-shift consumers exceeds the demand-supply gap on the 7th and 8th days in both schemes. However, the excess in the deterministic scheme is 20 MWh more than that in the stochastic scheme, indicating that the deterministic scheme wasted more resources. On the 10th day, the demand-supply gap is significantly higher. The deterministic scheme requires a power curtailment of 643 MW from fast-response consumers, while the stochastic scheme only needs 43 MW, resulting in considerably lower total power rationing costs.

4.3. Impacts of industrial chains on power rationing schedules

The proposed approach accounts for industrial chain coupling between upstream and downstream consumers, which can effectively reduce the total costs. As compared in Figure 7, if industrial chain is not considered, the total cost

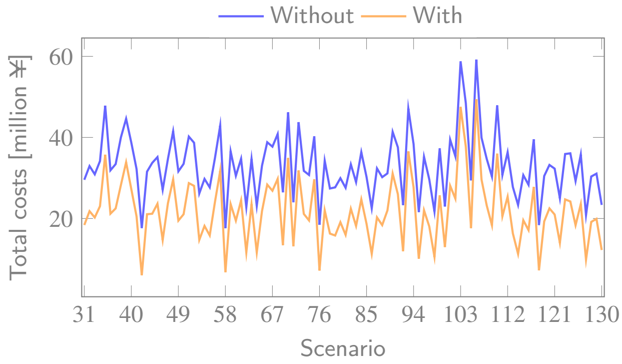
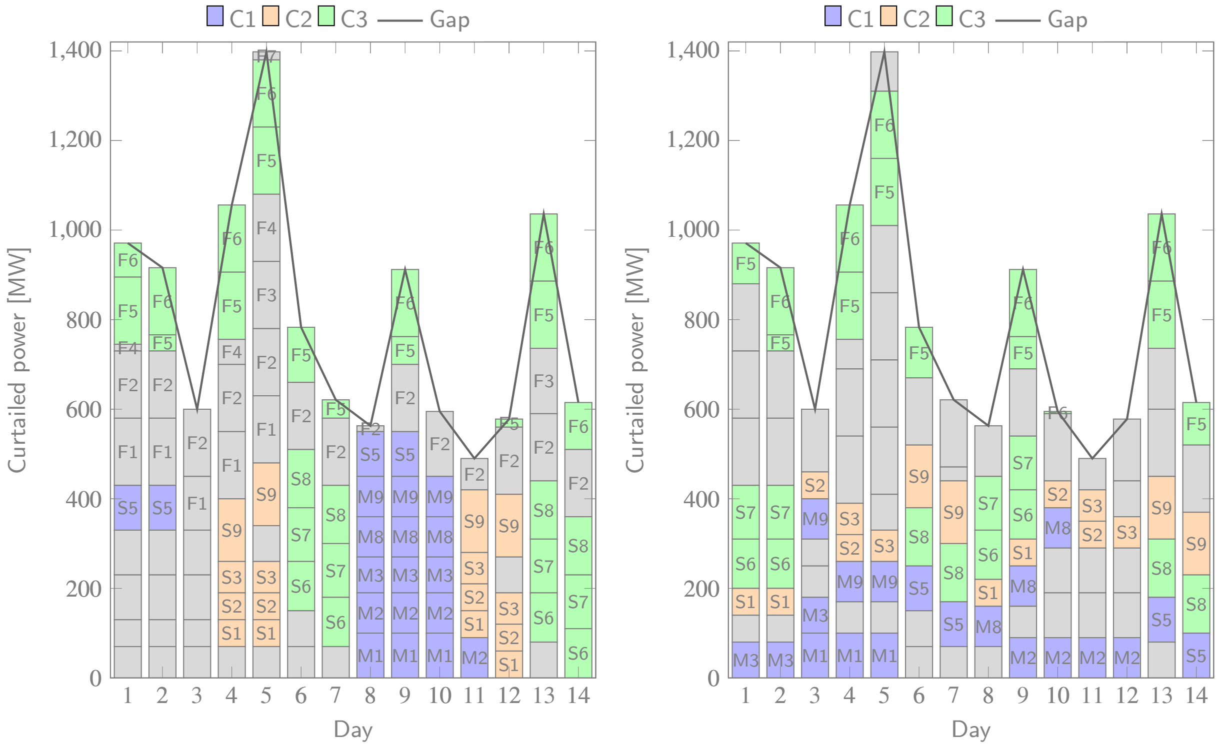


Figure 7: Comparison of total power rationing costs with and without consideration of industrial chains under different demand-supply gap scenarios.



(a) Considering industrial chains

(b) Not considering industrial chains

Figure 8: Power rationing schedules with (a) and without (b) consideration of industrial chains in scenario 35. SC1-3: three industrial chains; Gap: demand-supply gap.

increases by 19.8%∼193.5% with an average increase of around 51.8%. Figure 8 further compares the power rationing schedules considering and neglecting industrial chains in scenario 35. Blue, orange and green are used to represent industrial chains C1∼C3. Consumers coupled by industrial chains are labeled with the corresponding colors, while others are labeled with gray.

Maintenance consumers M1∼M3, M8∼M9 and work-shift consumer S5 are in industrial chain C1. More specially, M1 and M2 are in the upstream of M3, M8 and M9, while S5 is in the downstream of M3. In Figure 8a, M3, M8 and M9 are scheduled to conduct maintenance on days 8∼10, when M1 and M2 are also in maintenance. As for S5, days 8-9 are non-work days, and M3 is in maintenance on both days. By comparison, these consumers do not show clear

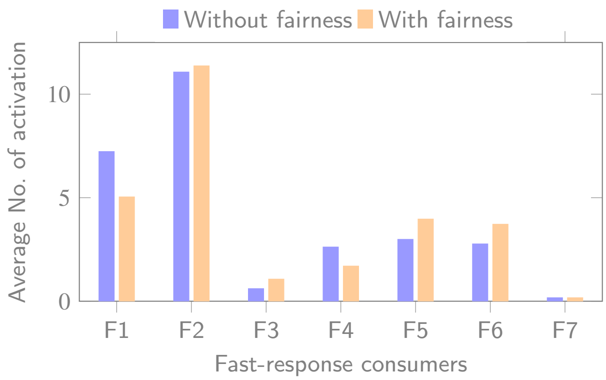


Figure 9: Average activation numbers of fast-response consumers in 100 scenarios.

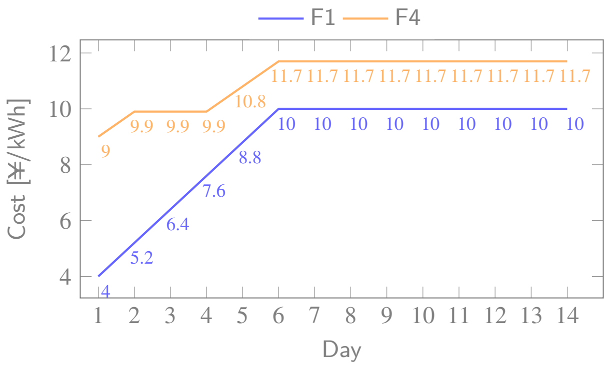


Figure 10: Evolution of activation costs of fast-response consumers F1 and F4 in scenario 35.

patterns in Figure 8b. With respect to industrial chain C2, work-shift consumers S1∼S3 are upstream consumers of S9, and all four consumers are scheduled for non-work days on day 4, 5, 11 and 12 in Figure 8a. Nevertheless, Figure 8b indicates uncoordinated schedules among them. In industrial chain C3, there exists two fast-response consumers F5 and F6 whose upstream consumers are S6∼S8. In Figure 8a, the power rationing of S6∼S8 are distributed on four days, and F5∼F6 are activated on these days. Whereas in Figure 8b, S6∼S8 are scattered on 8 days and the activation of F5∼F6 shows no pattern, leading to more costs. The analysis of three industrial chains concludes that accounting for industrial chains in the model leads to more coordinated power rationing schedules, thereby reducing the disruption to industrial chains and the associated costs.

4.4. Impacts of fairness on power rationing schedules

The activation of fast-response consumers can significantly disrupt real-time production plans on that day, so social fairness must be accounted for in addition to economic losses. A fairness factor and accumulated number of activations are used to adjust the total cost of activating a fast-response consumer, for the sake of relative fairness.

Figure 9 compares the average number of activations with and without fairness. If fairness is not considered, the number of activations is solely determined by economic cost. Fast-response consumers with relatively lower economic costs, such as F1 and F2, are activated frequently. However, when fairness is accounted for, the activation numbers of F1 and F4 decrease noticeably because their fairness coefficients are non-zero, indicating a strong disinclination to power rationing. Meanwhile, the activation numbers of other consumers increase due to their indifference to fairness.

Further insights into the impact of fairness on power rationing schedules can be gained by looking at Figure 8a and Figure 10 together. Initially, the total cost of activating F1 only constitutes economic cost, amounting to 4 ¥/kWh. However, it increases by 1.2 ¥/kWh as a social cost per activation. Similarly, F4 starts at 9 ¥/kWh and increases by 0.9 ¥/kWh per activation. In contrast, F2, F3, F5, F6 and F7 remain at 4 ¥/kWh, 10 ¥/kWh, 9 ¥/kWh, 9 ¥/kWh and 25

¥/kWh, respectively. On the 6th day, F2 and F5 are activated instead of F1 because F1 have been activated many times in the previous days, and its total cost has increased from 4 ¥/kWh to 10 ¥/kWh, exceeding the cost of F5. Likewise, F4 has increased to 11.7 ¥/kWh and is not activated as well. Therefore, by accumulating the number of activations for fast-response consumers, and incorporating the social cost into the total cost, fairness can be effectively promoted.

4.5. Categorizing consumers

Consumers are categorized into three types primarily based on their consumption characteristics, as introduced in section 3. However, it is acknowledged that some consumers may exhibit characteristics of multiple types. For example, approximately 40% of the demand in the non-ferrous metal smelting and rolling plant can be attributed to the dissolving furnace. Although the furnace's electricity demand can be curtailed within 30 minutes, it cannot be sustained for a long period while maintaining the required temperature. Conversely, if the consumer declares maintenance, up to 98% of the total demand can be curtailed. Thus, a trade-off exists where categorizing consumers as maintenance consumers offers greater curtailment potential at the expense of advance planning. By categorizing as many consumers as possible under maintenance and work-shift categories, production disruptions can be minimized, but this entails the risk of insufficient fast-response consumers available in real-time. Optimizing the consumer categorization would be a separate research endeavor, which is beyond the scope of this study.

Nevertheless, a sensitively analysis is conducted in this section. More specially, consumers M4∼M7 are re-categorized as fast-response consumers. To evaluate the cost implications of this re-categorization, the total costs across different scenarios are compared. The analysis reveals that, on average, the total costs increased by 4.9% with the re-categorization. Moreover, in 83 out of the 100 scenarios, the total costs experience an increase. This can be attributed to the fact that when more consumers are classified as fast-response consumers, they are unable to plan their power rationing schedules in advance. As a result, the 30-minute short notice causes higher costs. This finding underscores the trade-off between categorizing consumers as fast-response and the associated economic implications. While the responsiveness of fast-response consumers is advantageous in certain situations, it also introduces challenges and potential costs due to the lack of advance planning.

5. Conclusions

This paper proposes an optimization scheme for designing power rationing schedules, comprising a two-stage stochastic model to generate maintenance and work-shift schedules, and an activation model for fast-response consumers based on real-time demand-supply gaps. The proposed scheme is particularly well-suited for countries facing challenges with generation adequacy, where electricity markets are unable to effectively transmit accurate price signals to incentivize sufficient consumer demand reduction. In such cases, administrative power rationing becomes necessary. The scheme effectively addresses these issues and provides a viable solution for managing power demand-supply gaps in a long-term power shortage. Numerical simulations demonstrate the following conclusions:

(i) The two-stage stochastic model effectively deals with uncertainties in demand-supply gaps and coordinates three types of consumers at multiple time scales to provide power rationing schedules at lower costs, compared to the rolling blackout method and a deterministic model. The stochastic model outperforms the deterministic model in 79 out of 100 scenarios and reduces the average total costs by 2.96%.

(ii) By considering the impact factor of upstream consumers on downstream consumers, the model accurately reflects the coupling of industrial chains and minimizes disruptions caused by power rationing. The synchronized rationing of consumers within the same industrial chain significantly reduces total costs by 19.8%∼193.5% with an average of around 51.8%.

(iii) Introducing the fairness coefficient mitigates excessive activation of the same fast-response consumer by 30.1%∼35.2% in terms of average number of activations and relieves the social impact of power rationing. This is achieved by accumulating the number of activations for each consumer and incorporating social costs in addition to economic losses. The fairness coefficient promotes a more equitable distribution of power rationing, reducing the burden on specific consumers and fostering social stability.

Based on the discussion with practitioners, several recommendations related to practical implementation of this proposal are offered, which can facilitate the adaptation of this proposal in other countries.

(i) C_n is used to reflect the cost of power rationing and it should not rely on company profits for calibration. Power rationing is not like demand response, which is the autonomous reaction of a company based on economic incentives. Rather, it is an administrative decision and the cost concerned by the government is more of GDP or tax. Therefore, it is suggested to use the average tax or GDP per MWh to calibrate C_n. The data is relatively available for the industry that n belongs to, if not for n itself.

(ii) In the proposal, α_n is used to reflect industrial chain coupling. Unfortunately, information about the suppliers of n is often confidential, making it difficult to calibrate α_n accurately. On the one hand, industry-level data would be helpful for an estimation, but on the other hand, power rationing schedules are not sensitive to the exact values of α_n based on this study. What matters more is to consider industrial chain coupling in the model rather than the exact values of α_n.

(iii) Although fairness is a subjective concept, it is quantified by β_n in this study. It is suggested to assign similar initial values to β for consumers belonging to the same industry. Then, β_n could be adjusted based on how consumer n is supportive of power rationing. Practitioners have indeed mentioned that some consumers were very cooperative with their work, possibly due to a high awareness of social responsibility.

Some limitations of the proposed model and directions for future work are discussed as follows.

(i) The proposed scheme utilizes categorized consumers, but as discussed in section 4.5, some consumers may exhibit characteristics that align with multiple types. Therefore, it would be intriguing to develop models that optimize the categorization of consumers, taking into account their diverse characteristics.

(ii) While the proposed scheme adopts a two-stage stochastic programming model, it may not fully capture the dynamics of evolving demand-supply gaps. Employing a multiple-stage stochastic programming model could potentially yield better results. However, it is crucial to investigate more advanced algorithms that can address the challenges associated with the "curse of dimensionality" [35, 36].

(iii) Decomposition techniques would be required to tackle larger instances of the model, involving additional scenarios, more consumers, and an extended time horizon.

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CRediT authorship contribution statement

Yuting Mou: Conceptualization, Methodology, Software, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization. **Beibei Wang:** Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing. **Zhan Shen:** Investigation, Data Curation, Writing - Review & Editing.

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A. Nomenclature

A.1. Sets

$\mathcal{N}$, N Set of consumers and its cardinality

$\mathcal{N}^{\mathbf{M}}$ Set of maintenance consumers

$\mathcal{N}^{\mathbf{S}}$ Set of work-shift consumers

$\mathcal{N}^{\mathbf{MS}}$ Set of maintenance and work-shift consumers

$\mathcal{N}_n^{\mathbf{Up,MS}}$ Set of maintenance and work-shift consumers, who are in the same industrial chain as consumer n and in the immediate upstream, $n \in \mathcal{N}$

$\mathcal{N}^{\mathbf{F}}$ Set of fast-response consumers

$\mathcal{T}, T$ Set of time periods and its cardinality, includes morning peak and evening peak hours

$\mathcal{D}$ Set of days when power rationing is implemented

Ω Set of supply-demand gap scenarios

A.2. Parameters

P_n Maximum curtailable power of consumer n during power rationing, $n \in \mathcal{N}^{\mathrm{MS}}$, [MW]

C_n Cost of rationing consumer n, $n \in \mathcal{N}$, [¥/day/MW] $n \in \mathcal{N}^{\mathrm{MS}}$ or [¥/MWh] $n \in \mathcal{N}^{\mathrm{F}}$

$\underline{P}_{n,t}$ Minimum curtailable power of n in t, $n \in \mathcal{N}^{\mathrm{F}}$, $t \in \mathcal{T}$, [MW]

$\overline{P}_{n,t}$ Maximum curtailable power of n in t, $n \in \mathcal{N}^{\mathrm{F}}$, $t \in \mathcal{T}$, [MW]

$D_n^{\mathbf{M}}$ Maintenance duration (number of days) of consumer n, $n \in \mathcal{N}^{\mathrm{M}}$, [days]

$D^{\mathbf{S}}$ Number of non-workdays of work-shift consumers, [days]

$L_{t,d,\omega}$ Demand-supply gap in period t day d scenario ω, $t \in \mathcal{T}$, $d \in \mathcal{D}$, $\omega \in \Omega$, [MW]

Pr_{ω} Probability of scenario ω, unit free

α_n Impact factor of immediate upstream consumers on consumer n, $1 \leq \alpha_n \leq 1$, $n \in \mathcal{N}$, unit free

β_n Fairness factor of consumer n, $1 \leq \beta_n \leq 1$, $n \in \mathcal{N}^{\mathrm{F}}$, unit free

A.3. Variables

A.3.1. First-stage decision variables

$\mu_{n,d}$ Binary decision of consumer n in day d, in the state of power rationing or not, $n \in \mathcal{N}^{\mathrm{MS}}$, $d \in \mathcal{D}$, unit free

$v_{n,d}$ Binary decision of consumer n in day d, to start power rationing or not, $n \in \mathcal{N}^{\mathrm{MS}}$, $d \in \mathcal{D}$, unit free

$z_{n,d}$ Binary decision of consumer n in day d, to stop power rationing or not, $n \in \mathcal{N}^{\mathrm{MS}}$, $d \in \mathcal{D}$, unit free

p_n Curtailed power of consumer n during power rationing, $n \in \mathcal{N}^{\mathrm{MS}}$, [MW]

A.3.2. Second-stage decision variables

$\mu_{n,t,d,\omega}$ Binary decision of consumer n in period t day d scenario ω, in the state of power rationing or not, $n \in \mathcal{N}^{F}$, $t \in \mathcal{T}$, $d \in \mathcal{D}$, $\omega \in \Omega$, unit free

$p_{n,t,d,\omega}$ Curtailed power of consumer n in period t day d scenario ω, $n \in \mathcal{N}^{\mathrm{F}}$, $t \in \mathcal{T}$, $d \in \mathcal{D}$, $\omega \in \Omega$, [MW]