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Research Article

Research on Overconfidence in Decision-Making for the Capacity Recovery of Damaged Power Systems

Xing Bao[1,2]

[1] *Department of Business Administration, Zhejiang Institute of Administration, 1000 Wenyixilu, Hangzhou 311121, China*
[2] *Zhejiang Scientific Development Research Center, 1000 Wenyixilu, Hangzhou 311121, China*

Correspondence should be addressed to Xing Bao; goldbxing@gmail.com

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This paper studies the influence of two types of overconfident behavior, overestimation and overprecision, on decision of capacity recovery when power system's critical capacity is seriously damaged. A newsvendor model is used to prove that increasing regulatory punishment for electricity shortage and providing subsidy for capacity recovery are conducive measures to calibrate insufficient service level caused by an overconfident manager. The research also finds that the manager's overprecision behavior both negatively and positively influences the decision of capacity recovery, and a calibration method could motivate manager to recover more capacity by tuning up the ratio of punishment and subsidy. However, the effectiveness of the calibration mentioned above is inevitably weakened due to the less capacity recovery given by an overestimated manager. This research also indicates that the manager should pay close attention to the random disturbance whose distribution peak is left skewed, and correspondingly more capacity recovery should be given to improve the service level of power system during the disruption.

1. Introduction

Empirical researches in the field of knowledge management have found that a manager's confidence in the accuracy of his/her priori knowledge contributes to his/her decision-making when facing a complicated situation with incomplete information or highly fluctuated environment. A manager's intention and confidence to apply a priori knowledge may be strengthened when his/her observation of the situation is compatible with his/her knowledge (cf. [1]). A manager could strengthen his/her intention and confidence to apply a priori knowledge during decision by referring to past successful experiences, but this is not always the case. In an unexpected situation with extremely low probability, an overconfident and experienced manager may lose the capability to calibrate the accuracy of his/her a priori knowledge during the decision-making process (cf. [2]).

Some researchers have indicated that the more experience a manager has, the more likely he/she is to become overconfident in making decision (cf. [3]). In October 2012, the author of this paper conducted a survey of 50 senior managers of a district branch of the State Grid Corporation of China (SGCC) who suffered great disruption in the winter of 2008, nearly 75% of its critical transmission network was damaged by unexpected frozen rain, and it took over 2 weeks of recovery, which exceeded nearly one week than expected. After taking an in-depth interview with one of its senior managers in 2012, an interesting phenomenon was found: a large portion of mistakes were caused by middle-level managers who were making decision at the first line of disruption management. A successive interview with 50 middle-level managers was taken, and the results showed that 80% of the middle-level managers interviewed confessed that mistakes frequently happened in making decision during disruption management. However, it is interesting that most of the managers attributed the mistakes to their overconfidence in applying a priori knowledge. Similarly, the executives of Tokyo Electric Power Company (TEPCO) declined international assistance after the occurrence of the Fukushima Nuclear Accident in 2011. This was partly due to the fact that, as the world's leading nuclear power operator, TEPCO's executives overestimated their abilities of

disruption management, and as a result, there is a nuclear leakage crisis continuing to this day. For public infrastructures, such as electric power systems, rigorous regulations are enacted by the Government of China to ensure that managers of these systems are taking effective disruption management, for the purpose of securing and preserving the public interest as great as possible. However, in recent years, government officials and researchers have frequently realized the drawbacks of the existing regulations after the investigations of the 2003 blackout in the United States and Canada. According to the behavioral operation management (BOM) theory, the effectiveness of government regulations might be weakened, or even counteracted, due to the decision bias given by a bounded rational manager, particularly affected by an overconfident manager (cf. [4]). However, few studies have been conducted on the topic of how an overconfident behavior influences the manager's decision bias during the disruption. According to the knowledge of the author, this paper is the first disruption management study on the decision bias of an overconfident manager in the scenario that the critical capacity of a power system is seriously damaged by unexpected events. This paper also investigates the calibration methods, specifically regulatory punishment and subsidy, for the purpose of reducing the decision bias given by an overconfident manager during capacity recovery process.

This paper is organized into 6 sections. After the Introduction, relevant literatures on disruption management and overconfidence in operation management are reviewed as detailed as possible in Section 2. In Section 3, a newsvendor model corresponding to the disruption cost is firstly presented as a basic model that would be compared with the subsequent model of an overconfident manager. In Section 4, a modification to the newsvendor model mentioned in Section 3 is presented by two kinds of overconfident behaviors, overestimation and overprecision. And, corre-spondingly, the decision bias on capacity recovery is demonstrated. In Section 5, numerical simulations of capacity recovery decision biases are presented to illustrate the effects of random disturbances with the distribution functions being symmetrically and asymmetrically distributed. Finally, some interesting managerial insights and future researches are presented in Section 6.

2. Literature Review

In the past decade, operational systems and supply chains have frequently been crippled by unexpected catastrophes, such as natural disasters, human-made hazards, and terrorist attacks. Knowledge of traditional risk management is facing the challenges, because some unexpected events with extremely low probability have significant negative impacts on the whole supply chain from the disrupted node; thus, the huge negative consequences escalate quickly throughout the supply chain in a "snowball effect" (cf. [5]). Therefore, disruption management is focused on to reduce risks and expenses by researchers in recent years in the field of operation management.

Professor Sheffi may have been the first to research disruption management by conducting his studies on the security problems for international supply chains under the consideration of international terrorism (cf. [6]). Later, some researchers (e.g., Norrman, Hendricks, Oke, etc.) reviewed the mitigation strategies of lean supply chains through empirical and case studies in the context of disruption (cf. [7–9]). Some other researchers (e.g., Chopra, Kleindorfer, Zsidisin, etc.) presented disruption management frameworks of supply chains from the point of business continuity planning and flexible operation strategies (cf. [10–12]). Other researchers conducted studies through mathematical models of operation management, which follow the framework proposed by Tang (cf. [13]), based on the assumption that nodes of a supply chain might suffer disruptions. For example, in order to mitigate the disruption of main supplier, some researchers present selection models of supplier bases; the questions of how many suppliers are the best and when to start up the backup suppliers under different objective functions are investigated in detail in the consideration of cutting down the disruption cost while maintaining a certain service level (cf. [14–17]). To mitigate the cost in case of production capacity being disrupted, rescheduling algorithm is presented in order to get production plans that both operational cost and computation speed are satisfied in redispatching the residual capacity (cf. [18]), and to mitigate the risk in case of production capacity being disrupted, the decision of *ex-ante* preventive capacity investment or the short-term capacity trading strategy with partners is presented by multiobjective programming models (cf. [19]). Most of the mathematical models focus on the inventory strategies in case of disruption, for example, preventive inventory control strategies for managing supply chain disruption risk (cf. [20]), or performances of different inventory models and supply chain structures when facing transportation disruptions (cf. [21]), or optimal inventory policies with advanced warning of disruptions (cf. [22]). Other researchers have adopted game theory and contract theory to investigate incentive mechanisms or coordination policies that mitigate or prevent disruptions, for example, optimal subsidies for suppliers under a competitive manufacturing supply chain facing the disruptions of supplier bankruptcies (cf. [23]), or how a firm (buyer) can use incentive mechanisms to motivate a supplier's investment in capacity restoration, thus generating the restoration enhancement (RE) strategy or supplier diversification (SD) strategy when incentives are given *ex-ante* or *ex post* the supplier's disruption (cf. [24]), or how a disrupted supplier chose either to pay a penalty or to use backup production to manufacturer when supplier was privileged with private information (cf. [25]).

The mitigation strategies mentioned above generally assume that the "*decision- maker is completely rational*" throughout the entire cycle of disruption management, which does not account for the influence of bounded rationality on managers. If the bounded rationality of individuals in the decision-making process is neglected, a systematic bias will inevitably happen when compared to that of a completely rational model (cf. [26, 27]). When an experienced manager is making a decision, overconfidence is the most

Table 1: Notation descriptions in the proposed model.

D	Electricity demand of the public during disruption period
d	Residual capacity that can still be in operation after disruption and $d < D$
μ	Manager's decision of capacity recovery
$\overline{X}$	Random disturbance to capacity recovery process with its probability density and distribution functions of $f(x)$ and $F(x)$, respectively, with the mean and variance being φ and σ^2, respectively
k	Electricity shortage cost per capacity, which is also the regulatory punishment according to Electricity Regulatory Ordinance of China, given by regulation number 599
c_1	Recovery cost per damaged capacity
c_0	Operation cost per normal capacity
α	Factor of overestimation behavior of the manager
β	Factor of overprecision behavior of the manager

significant display of bounded rationality (cf. [28]), which is also validated by some behavioral experiments under the scenario of newsvendor decision (cf. [29–31]). However, mathematical models are not as common as empirical and experimental studies in the operation management field (cf. [32]). As far as the knowledge of the author, Croson et al. were pioneers who studied the decision bias by a newsvendor model of incorporating the overestimation and overprecision behaviors (cf. [33]). Inspired by the research of Croson (cf. [33]), this paper intends to study the capacity recovery decision through a newsvendor model when power system's capacity is damaged, of which the decision biases are investigated by considering the manager being overestimated and overprecise during disruption management. In addition, the calibration capability of regulatory punishment and subsidy in reducing the decision bias of capacity recovery is analyzed in detail, and managerial insights are presented by theoretical proofs and numerical simulations.

3. Description of Problems

It is assumed that the critical operation capacity of a power system is seriously damaged due to unexpected events, such as freezing rain, man-made sabotage, and operational mistakes, and as a result the service level is lowered and cannot satisfy the electricity demand of the public. In this case, the manager starts the recovery program at the first time in order to improve the service level of power system and to minimize operation and recovery costs during the disruption. Notations used in this paper are listed in Table 1.

Given that the recovery process can be fully controlled, the quantity of capacity recovery decision R is rather simple, and $R = D - d$. However, the fact is that random disturbance could change the capacity recovery decision. Therefore, $R = D - d + \overline{X}$, and $\overline{X}$ is the random disturbance with the mean and the variance being φ and σ^2, respectively, in which φ can be either positive or negative. Further, $R = D - d + \varphi + \sigma X = \mu + \sigma X$, where $X \sim (0, 1)$ is the standardized random disturbance with probability density and distribution function being $f(x)$ and $F(x)$, respectively. The mean and the variance of R are μ and σ^2, respectively. In this case, μ is the decision variable, which is assumed to be studied in the following sections.

It is assumed that the electricity demand of the public is fully satisfied by the operational capacity of the power system. The capacity per unit can meet the demand per unit, and excess capacity is unable to be lagged to the next period; thus, there is no electricity inventory cost. Therefore, a newsvendor model can be used to describe the operation cost $c(R)$, which the manager should balance during disruption:

$$c(R) = c_0 d + c_1 R + k[D - d - R]^+. \tag{1}$$

The substitution of $R = \mu + \sigma X$ into (1) gives the disruption cost function, with respect to the mean μ, as

$$C(\mu) = c_0 d + c_1 \mu + k \int_{-\infty}^{(D-d-\mu)/\sigma} (D - d - \mu - \sigma x) f(x)\, dx. \tag{2}$$

Hence, if a manager is completely rational, the optimal capacity recovery μ^* can be obtained by minimizing $C(\mu)$.

Proposition 1. *In the context of a completely rational manager, $C(\mu)$ is a convex function, and there is a unique $\mu^* = \max\{0, D - d - \sigma\lambda\}$ that makes $C(\mu^*) = \min C(\mu)$, where $\lambda = F^{-1}(c_1/k)$.*

Corollary 2. *μ^* is positively correlated with k, and is negatively correlated with c_1; that is, $\partial\mu^*/\partial k > 0, \partial\mu^*/\partial c_1 < 0$.*

Corollary 2 shows that, with the assumption of a rational manager, increasing k (e.g., increasing regulatory punishment for electricity shortage) and decreasing c_1 (e.g., providing subsidy for the recovery of damaged capacity) may strengthen the intention of manager to increase the decision of capacity recovery.

Proposition 1 also demonstrates that any bias away from μ^* will increase the disruption cost. In addition, according to Proposition 1 and Corollary 2, it can be seen that $\lambda = F^{-1}(c_1/k) = D - d - \mu^*/\sigma$ is virtually the upper quartile of the distribution function of X at the probability of c_1/k. And it is clear that (1) $d + \mu^* \geq D$ when $\lambda < 0$, which means that electricity demand can be fully satisfied during disruption; (2) $d + \mu^* < D$ when $\lambda > 0$, which means that there is electricity shortage during disruption. Corollary 2 indicates that increasing regulatory punishment (e.g., increasing k)

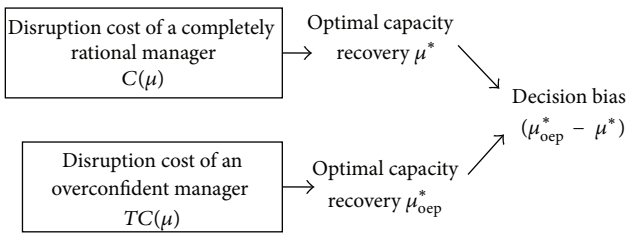

Figure 1: Decision bias model due to overconfidence.

and provision of subsidy for capacity recovery (e.g., reducing c_1) could help to improve power system's service level by increasing the final capacity (e.g., $d + \mu^*$) during disruption. Otherwise, an insufficient service level will be ensured by a low-capacity recovery decision.

4. The Decision Bias of an Overconfident Manager

According to the survey and interview conducted on 50 managers of a district branch of SGCC, very few managers could follow the decision provided by the $C(\mu)$ in a completely rational decision mode, which is described in Section 3. During disruption, an overconfident manager tends to make his/her decisions based on experiences of past successful practice. The more successful past experiences he/she has had, the more optimistically he/she will regard the random disturbance in the decision-making process. Therefore, an overconfident manager makes the decision of capacity recovery (e.g., μ^*_{oep}) by the cost function of $TC(\mu)$ that is given by Model II in Figure 1. Obviously, there is a decision bias of capacity recovery (e.g., $\mu^*_{\text{oep}} - \mu^*$) between Model I and Model II, and, thus, the disruption cost is increased in Model II.

Croson et al. proposed two types of overconfidence: overestimation and overprecision (cf. [33]), which are also followed by this research. First, overestimation will cause manager to make an overoptimistic estimation over the mean φ of external random disturbance; that is, $(D - d + \varphi)/\mu = \alpha \geq 1$, where α is the overestimation factor and $E(R) = \alpha\mu$. The greater the value of α is, the more overestimated the manager behavior is. Second, overprecision behavior would cause the manager to regard the random disturbance variance as $\text{var}(R) = [(1-\beta)\sigma]^2$, where β is the behavioral factor of overprecision. $\beta \to 0$ represents a manager with no overprecision behavior, and $\beta \to 1$ represents a completely overprecise manager.

It is difficult to distinguish between these two types of overconfidence that a manager may engage in decision-making during disruption. Therefore, this paper assumes that both of these two ways of overconfident behavior are taking into effects, and the impact on the decision bias of capacity recovery would be presented by modifying the model of Section 3. Furthermore, the calibration of reducing decision bias will be reinvestigated under an overconfident manager.

Accordingly, the capacity recovery decision made by an overestimated and overprecise manager is R_{oep}, and $R_{\text{oep}} = \alpha\mu_{\text{oep}} + (1-\beta)\sigma X$, with its mean and variance being $E(R_{\text{oep}}) = \alpha\mu_{\text{oep}}$ and $\text{var}(R_{\text{oep}}) = [(1-\beta)\sigma]^2$, respectively, where $\alpha \geq 1$ and $0 \leq \beta \leq 1$. Correspondingly, the disruption cost function takes the form of $TC_{\text{oep}}(\alpha\mu_{\text{oep}}, \alpha, \beta)$ according to Model II, as (3), where $U = (D - d - \alpha\mu_{\text{oep}})/(1-\beta)\sigma$:

$$\begin{aligned} TC_{\text{oep}}&\left(\alpha\mu_{\text{oep}}, \alpha, \beta\right) \\ &= c_0 d + c_1 \alpha\mu_{\text{oep}} \\ &\quad + k\int_{-\infty}^{U}\left(D - d - \alpha\mu_{\text{oep}} - (1-\beta)\sigma x\right) f(x)\,dx. \end{aligned} \tag{3}$$

Proposition 3. *The disruption cost $TC_{oep}(\alpha\mu_{oep}, \alpha, \beta)$ given by Model II is convex in μ_{oep}, and there is a unique $\mu^*_{oep} = (\mu^*/\alpha) + (\beta\sigma\lambda/\alpha)$ that yields $TC_{oep}(\mu^*_{oep}, \alpha, \beta) = \min TC_{oep}$.*

The proof of Proposition 3 is similar to that of Proposition 1 and is omitted herein.

Corollary 4. *The decision bias $(\mu^*_{oep} - \mu^*)$ is negatively correlated with α; that is, $\partial(\mu^*_{oep} - \mu^*)/\partial\alpha \leq 0$ and $\partial^2(\mu^*_{oep} - \mu^*)/\partial\alpha^2 \geq 0$, and the absolute decision bias has a positive correlation with β; that is, $\partial|\mu^*_{oep} - \mu^*|/\partial\beta = |\sigma\lambda/\alpha| \geq 0$.*

Corollary 5. *μ^*_{oep} is positively correlated with k while being negatively correlated with c_1; that is, $\partial\mu^*_{oep}/\partial k \geq 0$ and $\partial\mu^*_{oep}/\partial c_1 \leq 0$, respectively. The decision bias $(\mu^*_{oep} - \mu^*)$ is negatively correlated with k and positively correlated with c_1; that is, $\partial(\mu^*_{oep} - \mu^*)/\partial k \leq 0$ and $\partial(\mu^*_{oep} - \mu^*)/\partial c_1 \geq 0$. The cost bias $TC_{oep}(\mu^*_{oep}) - C(\mu^*_{oep})$ is linearly independent of (α, β) and is convex in α and β, respectively.*

Hereto, this paper has addressed the mathematical model modified by overestimation and overprecision behavior and proofs of decision bias with respect to parameters of punishment and subsidy. Furthermore, three inferences can be obtained through Corollaries 2 to 5.

Inference 1. When $\alpha > 1$ and $\beta = 0$, that is, managers only present the behavior of overestimation, α will cause decision bias of capacity recovery through the "multiplicative effect;" that is, $\mu^*_{\text{oe}} = \mu^*/\alpha$. α will inevitably lead to the decrease of the decision of capacity recovery, that is, $(\mu^*_{\text{oe}} - \mu^*) = ((1-\alpha)/\alpha)\mu^* < 0$, which may cause the power system to have a low service level during disruption. Furthermore, $\partial(\mu^*_{\text{oe}} - \mu^*)/\partial\alpha = -\mu^*/\alpha^2 < 0$, which means that even less capacity recovery is decided when α increases.

Inference 2. When $\alpha = 1$ and $\beta \neq 0$, that is, managers only present the behavior of overprecision, β will cause decision bias of capacity recovery through the "additive effect;" that is, $\mu^*_{\text{op}} = \mu^* + \beta\sigma\lambda$. Considering that $\lambda = F^{-1}(c_1/k)$, the decision bias, that is, $(\mu^*_{\text{op}} - \mu^*)$, is dependent on both the distribution of X and the ratio c_1/k. When $\lambda > 0$, factor of β would cause the increasing of the capacity recovery and relieve the negative bias caused by α. In contrast, when $\lambda < 0$, factor of β may further decrease the capacity recovery and deepen the

Table 2: Decision bias ($\mu^*_{\text{oep,lft}} - \mu^*_{\text{oep,nml}}$) for left-skewed disturbance.

	$\beta = 0.0$	$\beta = 0.2$	$\beta = 0.4$	$\beta = 0.6$	$\beta = 0.8$
$\alpha = 1.0$	0.0341	0.0509	0.1019	0.1528	0.2038
$\alpha = 1.2$	0.0404	0.0849	0.1274	0.1699	0.2123
$\alpha = 1.4$	0.0736	0.1091	0.1456	0.1819	0.2183
$\alpha = 1.6$	0.0984	0.1272	0.1592	0.1911	0.2824
$\alpha = 1.8$	0.2078	0.1800	0.1698	0.1983	0.2794

Table 3: Decision bias of ($\mu^*_{\text{oep,rgt}} - \mu^*_{\text{oep,nml}}$) for right-skewed disturbance.

	$\beta = 0.0$	$\beta = 0.2$	$\beta = 0.4$	$\beta = 0.6$	$\beta = 0.8$
$\alpha = 1.0$	−0.0673	−0.09665	−0.1933	−0.29	−0.3866
$\alpha = 1.2$	−0.0806	−0.1611	−0.2416	−0.3221	−0.4027
$\alpha = 1.4$	−0.1384	−0.2071	−0.2757	−0.3452	−0.4142
$\alpha = 1.6$	−0.1816	−0.2418	−0.3019	−0.3621	−0.4233
$\alpha = 1.8$	−0.2152	−0.23	−0.3222	−0.3757	−0.4292

negative bias caused by α, thus causing a lower service level when compared to that when $\alpha = 1$.

Inference 3. Given $\partial(\mu^*_{\text{oep}} - \mu^*)/\partial k \leq 0$ and $\partial(\mu^*_{\text{oep}} - \mu^*)/\partial c_1 \geq 0$, the regulators can calibrate the decision bias aroused by manager's overconfident behavior through increasing regulatory punishment for capacity shortage (i.e., increasing k) and providing subsidy for capacity recovery (i.e., decreasing c_1). However, close attention should be paid to the distribution function of random disturbance and the sign of λ. When the random disturbance is normally distributed and $c_1/k > 0.5$, an overconfident manager will generally increase the decision of capacity recovery. Otherwise, capacity recovery will be decreased. In addition, it should be noted that $\mu^*_{\text{op}} = D - d$ is independent of k and c_1 when $\beta = 1$, which means that punishment and subsidy from regulators will become completely invalid.

5. Numerical Analysis

Decision given by an overconfident manager is investigated by a modified newsvendor model, which could be easily evaluated by first- and second-order moments model of $\mu^*_{\text{oep,nml}} = D - d + z\sigma$, wherein z is the z-value given by the value of c_1/k by assuming that the random disturbance is normally distributed. However, this is not always the case, since many random disturbances present to be asymmetrically distributed with their peaks of distribution functions being left- or right-skewed from the mean value, which means that the third- and fourth-order moments of disturbance would take in function in evaluating μ^*_{oep}. Thus, neglecting the skewness of the random disturbance X will cause additional bias away from μ^*_{oep} (cf. [34]).

In the numerical analysis below, $\mu^*_{\text{oep,nml}}$ is supposed to be the recovery decision given by an overconfident manager, which is also served as the baseline when actual disturbance is not symmetrically distributed. $\mu^*_{\text{oep, lft}}$ and $\mu^*_{\text{oep,rgt}}$ are the capacity recoveries when the peaks of random disturbance distribution are left- and right-skewed, respectively. The skewed random disturbance is given by a partial student distribution expressed as

$$f(z_t \mid \xi, \nu) = \begin{cases} \dfrac{2}{\xi + 1/\xi} sg\left[\xi\left(sz_t + m\right) \mid \nu\right], & z_t < -\dfrac{m}{s}, \\ \dfrac{2}{\xi + 1/\xi} sg\left[\dfrac{\left(sz_t + m\right)}{\xi} \mid \nu\right], & z_t > -\dfrac{m}{s}, \end{cases} \tag{4}$$

where $s = \xi^2 + (1/\xi^2) - 1 - m^2$, $m = (\Gamma[(\nu-1)/2]\sqrt{\nu-2}/\sqrt{\pi} \cdot \Gamma(\nu/2)) \cdot (\xi - 1/\xi)$, $g[\cdot \mid \nu]$ is a symmetric student distribution, and ν is the parameter of fat-tail. When $0 < \xi < 1$, $f(z_t \mid \xi, \nu)$ is left-skewed, while $\xi > 1$, $f(z_t \mid \xi, \nu)$ is right-skewed. $\nu = 5$, $\xi = 0.5$, and $\xi = 2$ are set with the skewness of 2.1 to the left and to the right correspondingly. Other parameters used in numerical analysis are taken as $d = 1$, $D = 5$, $\sigma = 2$, $c_0 = 2$, $k = 10$, $c_1 = 6$. Tables 2 and 3 show the numerical results for the biases of ($\mu^*_{\text{oep, lft}} - \mu^*_{\text{oep,nml}}$) and ($\mu^*_{\text{oep,rgt}} - \mu^*_{\text{oep,nml}}$), respectively.

From Table 2, we can see that capacity recovery is less for a left-skewed random disturbance than that for a normal distributed disturbance; that is, $\mu^*_{\text{oep,nml}} < \mu^*_{\text{oep, lft}}$. However, $\mu^*_{\text{oep,nml}} > \mu^*_{\text{oep,rgt}}$ according to numerical results given by Table 3. It is largely the result that the negative effect of a left-skewed random disturbance is relatively underestimated by manager who uses the evaluation of $\mu^*_{\text{oep,nml}}$ instead, and it should be offset by a positive calibration value on $\mu^*_{\text{oep,nml}}$ in order to improve the service level during disruption, while the negative effect of a right-skewed random disturbance is relatively overestimated by manager when using $\mu^*_{\text{oep,nml}}$ instead, and more capacity recovery decision is foreseen, which would obviously increase the service level of power system during disruption. As a consequence, replacing $\mu^*_{\text{oep,rgt}}$ with $\mu^*_{\text{oep,nml}}$ could be regarded as having no harm to the interest and welfare of the public.

6. Managerial Insights and Future Research

In this paper, decision bias of capacity recovery is investigated under the scenario of power system's capacity being damaged by unexpected events. Modified newsvendor models are presented to show the decision bias given by an overconfident manager and a completely rational manager, respectively. And several interesting managerial insights as well as calibration methods for improving performance of disruption management are obtained through theoretical proofs and numerical simulations, which are given as below.

Firstly, for the sake of improving the power system's service level during disruption, regulators should increase regulatory punishment for electricity shortage and provide subsidy for capacity recovery at the same time, in order to calibrate the decision biases in reducing the capacity recovery by an overconfident manager. In other words, "*carrot-and-stick*" regulatory mechanism could push managers to recover more damaged capacity. Moreover, fortunately, "*carrot-and-stick*" regulatory mechanism can be always in function no matter the manager is overconfident or not.

Secondly, a manager's overestimation behavior will inevitably lower the decision of capacity recovery; thus, calibration capability of "*carrot-and-stick*" regulatory mechanism could be inevitably weakened, and a lower service level would be foreseen during the disruption of power system. For the interest and welfare of the public, higher punishment for electricity shortage should be prescribed by regulation to improve electricity service level in case of the manager being overconfident.

Thirdly, manager's overprecision behavior may have both negative and positive influences on the capacity recovery decision. More capacity recovery would be decided when the value of the upper quartile $\lambda = F^{-1}(c_1/k)$ of random disturbance is positive; otherwise, less capacity recovery would be decided. Furthermore, for improving the power system's service level during disruption, regulator should pay close attention to ensuring that the ratio c_1/k is less than 50%, which indicates that capacity recovery cost after subsidy must be less 50% the value of punishment for electricity shortage.

Finally, negative impact on capacity recovery would be underestimated under a left-skewed disturbance, and lower electricity service level would be caused due to the decision of less capacity recovery. In contrast, higher electricity service level would be foreseen due to the decision of more capacity under right-skewed disturbance and normal distributed disturbance, respectively. As a result of requiring higher electricity service level by regulator, the situation of right-skewed disturbance should be closely paid attention to by a manger during disruption management.

However, two assumptions made in this paper are expected to be relaxed in future modeling research. The first assumption is that this paper only studies exogenous punishment of electricity shortage, and it would be desirable to investigate an endogenous punishment given by a game model between regulator and manager. The second assumption is that the capacity recovery decision of Model II only considers a single period; however, the overconfident behavior might be changed during the disruption, and thus the correlations of decision between neighboring periods during disruption should be investigated in future research despite the difficulties in creating mathematical model.

Appendix

Proof of Proposition 1. Taking the first and the second derivatives of $C(\mu)$ with respect to μ, we can obtain $\partial C(\mu)/\partial\mu = c_1 - kF((D-d-\mu)/\sigma)$, $\partial^2 C(\mu)/\partial\mu^2 = (k/\sigma)f((D-d-\mu)/\sigma)$. Since $\partial^2 C(\mu)/\partial\mu^2$ is nonnegative, $C(\mu)$ is a convex function, and the optimal solution of μ^* can be derived from $\partial C(\mu)/\partial\mu = 0$; that is, $\mu^* = D-d-\sigma F^{-1}(c_1/k)$. Since μ^* is nonnegative, then $\mu^* = \max\{0, D-d-\sigma\lambda\}$. □

Proof of Corollary 2. Based on Proposition 1, taking the first derivative of μ^* with respect to k and c_1 yields $\partial\mu^*/\partial k = \sigma F(\lambda)/kf(\lambda) > 0$, $\partial\mu^*/\partial c_1 = -\sigma/kf(\lambda) < 0$. □

Proof of Corollary 4. According to Proposition 3, $(\mu^*_{\text{oep}} - \mu^*) = \mu^*/\alpha + \beta\sigma\lambda/\alpha - \mu^*$ when $\mu^* + \beta\sigma\lambda > 0$. Its first-order derivative with α is $\partial(\mu^*_{\text{oep}} - \mu^*)/\partial\alpha = (-1/\alpha^2)(\mu^* + \beta\sigma\lambda) \le 0$. Similarly, the second-order derivative with α is $\partial^2(\mu^*_{\text{oep}} - \mu^*)/\partial\alpha^2 = (1/\alpha^3)(\mu^* + \beta\sigma\lambda)^2 \ge 0$. Similarly, $\partial(\mu^*_{\text{oep}} - \mu^*)/\partial\beta = \sigma\lambda/\alpha$, and it can be easily obtained that the sign of $(\mu^*_{\text{oep}} - \mu^*)$ depends on λ. The absolute decision bias is nonnegative; that is, $\partial|\mu^*_{\text{oep}} - \mu^*|/\partial\beta = |\sigma\lambda/\alpha| \ge 0$. □

Proof of Corollary 5. According to Proposition 3, it can be obtained that $\partial\mu^*_{\text{oep}}/\partial k = (1/\alpha)((\partial\mu^*/\partial k) + \beta\sigma(\partial\lambda/\partial k)) = \sigma(1-\beta)F(\lambda)/\alpha kf(\lambda) \ge 0$, $\partial\mu^*_{\text{oep}}/\partial c_1 = \sigma(\beta-1)/\alpha kf(\lambda) \le 0$. It can also be obtained that $(\partial\mu^*_{\text{oep}}/\partial k) - (\partial\mu^*/\partial k) = -\sigma(\alpha + \beta - 1)F(\lambda)/\alpha kf(\lambda) \le 0$, $(\partial\mu^*_{\text{oep}}/\partial c_1) - (\partial\mu^*/\partial c_1) = \sigma(\alpha + \beta - 1)/\alpha kF(\lambda) \ge 0$. Similarly, it could be obtained that $\partial(TC_{\text{oep}} - C)/\partial\alpha = \mu^*_{\text{oep}}[c_1 - kF(U)]$, $\partial(TC_{\text{oep}} - C)/\partial\beta = \sigma k\int_{-\infty}^{U} xf(x)dx$, and then $\partial^2(TC_{\text{oep}} - C)/\partial\alpha^2 = (\mu^2_{\text{oep}}/(1-\beta)\sigma)kf(U) \ge 0$, $\partial^2(TC_{\text{oep}} - C)/\partial\beta^2 = (\sigma/(1-\beta))kU^2 f(U) \ge 0$, $\partial^2(TC_{\text{oep}} - C)/\partial\alpha\partial\beta = -(\mu^*_{\text{oep}}/(1-\beta))kUf(U)$. It can be derived that the Hessian matrix is 0. Therefore, the cost bias $TC_{\text{oep}}(\mu^*_{\text{oep}}) - C(\mu^*_{\text{oep}})$ is linearly independent of (α, β), and fortunately $TC_{\text{oep}}(\mu^*_{\text{oep}}) - C(\mu^*_{\text{oep}})$ is convex in α and β, respectively. It means that the influences of α and β on the disruption cost bias are independent of each other. The calibration methods on α would have no influence on those on β. □

Conflict of Interests

The author declares that there is no conflict of interests regarding the publication of this paper.

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