A dual capacity sourcing model of disruption management for an injured power system

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Abstract

Great loss would be caused when power system lost its critical capacity by the impact of extreme events. Disruption management of State Grid Zhejiang Electric Power Company of China (shorted for SGZEPC) suffered in 2008 was firstly investigated, and then a dual sourcing model of regular and expedite capacity during recovery periods is correspondingly presented in this paper. A mathematical model of capacity procurement in a multi recover periods is constructed at the aim of minimizing the disruption cost of injured power system. Three meaningful managerial insights are obtained through sensitivity analysis on key parameters, which is helpful for manager to make decision during the disruption period.

Keywords: disruption management, injured power system, dual capacity sourcing, multi-period

1 Introduction

Power system is one of most important public facilities which highly relies on the safety and steady operation of its critical capacities, such as power transmission network, distribution facilities and power plants. Despite a lot of protection on its safety operation have been done, power system still cannot eliminate every potential threats arose by unexpected events, such as natural disasters, man-made operational defaults and even intentional attacks.

In recent years, serious blackouts were frequently witnessed that power systems lost their critical capacities. For example, State Grid Zhejiang Electric Power Company of China (shorted for SGZEPC) suffered great loss on its operation history, because of a hundred-year frozen rain attacked its transmission network in Jan 2008, and about 75 percent of its power transmission lines were crippled by heavy ice. This unexpected frozen rain caused a serious blackout among Zhejiang Province of China, which caused the consequence of over 20 million people suffered power shortage for over two weeks. Disruption management was started at the first time, Manager of SGZEPC on one hand started recovery process on the injured capacity, on the other hand acquired as much as possible the temporary electricity from its neighbouring provincial partners and mobile generators.

In this paper, we would like to present a multi-period model under the scenario of SGZEPC's disruption management in 2008. The paper is organized as follows: In section 2, the most related literatures to our research are reviewed. In section 3, the basic description and notations of our model are presented according to our background case. In section 4, the mathematical model and proofs of optimal decision sequences are presented at the aim of minimizing the disruption cost. In section 5, sensitivity analyses on key parameters of our model are given to illustrate the impaction on disruption cost. Finally, managerial insights and conclusions are presented in section 6.

2 Literature review

In the past decade, many researchers in the fields of operation management and risk management have done voluminous studies in order to enhance the system's operational robustness in facing fluctuations from both inside and outside [1]. However, some researchers argued that some traditional risk mitigation methods should be reinvestigated under the scenario of operation system (or supply chain) might be attacked by those unexpected events, because of "Snow Ball" effects could cause risks spreading quickly along the whole supply chain from the disrupted node [2]. Losses caused by abnormal disruptions are much more serious that those caused by normal risks (operational risk, seasonal fluctuation risk et al). Different from those traditional risk management researches, disruption management puts more emphasis on risks arose by those unexpected events with great negative impacts and extremely low probabilities. Researches exist in disruption management nowadays can be categorized into two streams. The first stream adopts the methodologies of empirical and framework studies, for one purpose is to verify whether disruption really has negative impact both on company's long-term performance through statistical models or cases [3-4], and

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for another purpose is to introduce disruption mitigation methods, guidelines and strategies through framework models [5-6]. The second stream attracts the most of researchers in giving mathematic models and simulations in order to give some effective mitigation methods before\during\after the break out of disruption, and much of the works follow the framework of [1].

Once the disruption happens on the critical capacity of power system, there three kinds of mitigation methods in operational level that manager could take [5]. They are lagging demand along the time scale by price coordination [7], increasing temporary capacity by sourcing from suppliers or partners [8-9], and mitigation the cost by production rescheduling [10-11]. Although disruption cost could be greatly cut down, the mitigation methods/policies are always confined by the operation system's public importance. For example, shifting the demand to the future time span may alleviate the current shortage of capacity by increasing the price temporarily [12]. However, this might not be a good idea, because increasing the electricity spending might easily incur the protest or pressure from the public or government [13]. Procuring or sourcing inventory from backup suppliers or capacity-sharing partners are extensively studied in supply disruption management, and how to make the best order-split decisions among different suppliers are mainly focused [14-18]. We are glad to find that dual capacity sourcing described in [14] was still adopted by SGZEPC in 2008 when acquiring temporary electricity during the disruption management. For example, temporary electricity was provided from its neighbouring provincial power system and mobile generators. However, capacity damage are much more serious than capacity shortage, which could causes a sharp fall in the service level and contributes great loss towards the power system. Following this point of view, some researchers paid their attention to generate sub-optimal operational plans/ routings by dispatch the residual capacity in order to obtain a satisfied cost as well as save the calculation time [19-20]. However, the assumption of recovered capacity can be only reused at the last period might not be proper according to the practice of SGZEPC, because recovered capacity was gradually put into reoperation during the disruption periods [21]. Thus, we are inspired to make a further extension of [21] under the scenario of power system's injured capacity is gradually recovered.

3 Problem description and notation

According to the practice of SGZEPC in 2008, electricity provision in Zhejiang province is seriously deteriorated due to the injury of critical capacity. SGZEPC started the procedure of disruption management at first time. On one hand, the injured capacity should be recovered to normal state; on the other hand, the service level of electricity provision should be tried best to keep in certain satisfied level by acquiring more temporary electricity from both inside and outside of SGZEPC's operation system. There were two kinds of capacity that could SGZEPC provide extra electricity. For example, regular capacity was procured form its neighbouring provincial partners through SGZEPC's residual capacity, and the expedite capacity was procured by starting the backup power systems, such as mobile generators. Therefore, the disruption management model could be illustrated in figure 1.

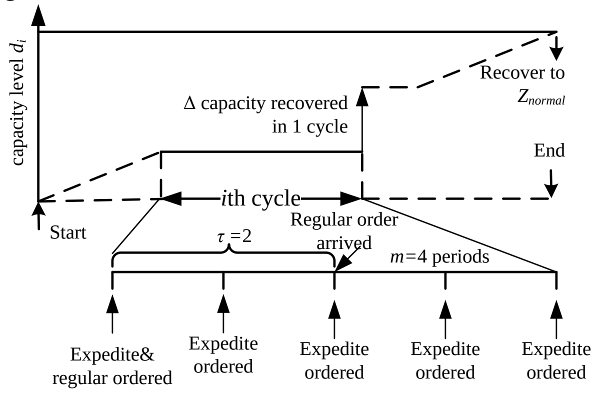

FIGURE 1 Disruption management model when operation capacity is injured

For convenience of creating mathematical model, notations are described as bellow:

Z_{normal} is the power system's planned capacity in normal state.

d_0 is the residual capacity that is still in operation when disruption take place, and $d_0 < Z_{normal}$.

N is the recovery cycles that is needed to recover all the injured capacity to normal state Z_{normal}, and there are m periods in 1 cycle.

r is the recovered capacity in 1 recovery cycle which is bounded by recovery technique, and $\Delta = \left(Z_{normal} - d_0\right)/N$ is the recovery up-limit. Further, we assume $\Delta = r$. Recovered capacity need m periods that can be put into re-operation. In other words, recovered capacity can only be reused at every end of recovery cycle.

$P(\Delta)$ is recovery cost function.

U is regular capacity that capacity-sharing partner could provide, and is ordered only once at the beginning of each cycle with a fixed value. U is received after τ periods, therefore, τ is the lead time of regular capacity, where $2 \le \tau \le m$.

y is electricity demand in each period, and y is a non-negative random variable with the probability density and distribution function are $f(y)$ and $F(y)$ respectively. Electricity demand is satisfied by the output of system's capacity at the end of each period and unit capacity satisfied unit demand. Unsatisfied demand is backlogged to next period.

The subscript (i, j) is a time indicator which means i^{th} cycle and j^{th} period, and $i = 1,...,N$, $j = 1,...,m$. Some additional notations are defined as follows:

$z_{i,j}$ is the planned capacity in (i,j) period which is a decision variable, where $0 \le z_{i,j} \le d_i$ when $j = 1,...,m-1$, and $0 \le z_{i,j} \le d_i + \Delta$ when $j = m$.

$v_{i,j}$ is the quantity of expedite capacity procurement, which is ordered at the beginning of each period and received at the end of each period, therefore the lead time of $v_{i,j}$ is set to 1 period. Additionally, $0 \le v_{i,j} \le V$, where V is the maximum that expedite capacity could be acquired.

$x_{i,j}$ is the net inventory at the beginning of (i,j) period, demand that was not satisfied in last period is backlogged. $x_{i,j}$ is also the state transition variable, and $x_{i,j} = \min\{0, x_{i,j}\}$ which means excessive electricity cannot be backlogged into next period.

c_0 is the unit cost of using system's own capacity. c_1 and c_2 are the unit cost of using regular and expedite capacity respectively, the expedite capacity is much more expensive, thus $c_1 < c_0 < c_2$.

k is the unit shortage cost when electricity cannot meet the demand.

α is the manager's risk attitude factor during the disruption periods, which take the form of equation (1). Manager will be more aggressive in using expedite capacity $v_{i,j}$ when α increases. Otherwise, decision maker will be more conservative when α decreases.

$$\alpha = \frac{v_{i,j}}{Z_{normal} - z_{i,j}} \tag{1}$$

4 Mathematic model

Based on the description of section 2, we could construct the cost function $\phi_{i,j}$ in normal state as equation (2), where the first item is operation cost of planned capacity, the second item is electricity shortage cost.

$$\phi_{i,j} = c_0 z_{i,j} + k(z_{i,j} - y)^- \tag{2}$$

It is rather interesting that $\phi_{i,j}$ is obviously a newsvendor model. Thus, we could easily obtained the optimal planned capacity $z^*_{i,j}$ in normal state by minimizing the expectation cost of equation (2), and $z^*_{i,j}$ is regarded as Z_{normal} as equation (3), where $F^{-1}(\cdot)$ is the inverse function of $F(\cdot)$.

$$Z_{normal} = F^{-1}(1 - \frac{c_0}{k}) \tag{3}$$

Further, we could construct the cost function during the disruption period (i,j) as equation (4), where the second item is the procurement cost of regular capacity, the third is procurement cost of expedite capacity, and the last item is injured capacity recovery cost.

$$\begin{aligned}\varphi_{i,j} = {} & c_0 z_{i,j} + c_1 U\delta(j-\tau) + c_2 v_{i,j} + k[x_{i,j-1} + z_{i,j} + v_{i,j} + \\ & U\delta(j-\tau) - y]^- + P(\Delta)\end{aligned} \tag{4}$$

$\delta(\cdot)$ is dirichlet function, where $\delta(0) = 1$ when $j = \tau$, otherwise $\delta(\cdot) = 1$ when $j \ne \tau$. $x_{i,j}$ in equation (4) is the state transition function, which takes the form as equation (5).

$$x_{i,j} = \min\{x_{i,j-1} + z_{i,j} + v_{i,j} + U\delta(j-\tau) - y, 0\} \tag{5}$$

The expectation disruption cost of equation (5) takes the form as equation (6), where $\theta = x_{i,j-1} + z_{i,j} + v_{i,j} + U\delta(j-\tau)$.

$$\begin{aligned}\Phi_{i,j} = {} & c_0 z_{i,j} + c_1 U\delta(j-\tau) + c_2 v_{i,j} + \\ & k\int_{y=\theta}^{\infty} (y-\theta) f(y)dy + P(\Delta)\end{aligned} \tag{6}$$

It can be easily proved that $\Phi_{i,j}$ is convex in $z_{i,j}$, so we omit the proof. And we could get the optimal planned capacity $z^*_{i,j}$ in period (i,j) by solving $\frac{\partial \Phi_{i,j}}{\partial z_{i,j}} = 0$, and the expedite capacity can be obtained through equation (1), that is $v^*_{i,j} = \alpha(Z_{normal} - z^*_{i,j})$, which is obvious an "*order up to*" decision.

However, due to the net inventory variable $x^*_{i,j}$, we could not expect the optimal decision $[z^*_{i,j}, v^*_{i,j}]$ in single period to be also optimal in a multi-period decision. Here, we define a cost function $J_{i,j}(x,z,v)$, which is a total expected cost by aggregating expected discounted from $(i,j)^{th}$ period to the (N,m) period. And $J_{i,j}(x,z,v)$ takes the form of equation (7).

$$J_{i,j}(x,z,v) = \Phi_{i,j} + \rho \min\{J_{i,j+1}(x,z,v)\} \tag{7}$$

ρ is discounted cost which is set to 1 in the following equations. Further, let $T_{i,j+1}(x,z,v) = \min\{J_{i,j+1}(x,z,v)\}$, then we could obtain $J_{i,j}(x,z,v)$ as equation (8):

$$\begin{aligned}J_{i,j}(x,z,v) = {} & c_0 + c_1 U\delta(j-\tau) + c_2 v_{i,j} + \sum\nolimits_1^i P(\Delta) + \\ & k\int_{y=\theta}^{\infty} (y-\theta) f(y)dy + \int_{y=0}^{\infty} T_{i,j}(\theta - y) f(y)dy\end{aligned} \tag{8}$$

Proposition 1: $T_{i,j}(x,z,v)$ is convex in $x_{i,j}$, $z_{i,j}$ and $v_{i,j}$.

Proof: Backward induction is adopted in proving proposition 1. Firstly, expectation cost of last period $J_{N,m} = \Phi_{N,m}$, and it can be easily proved that $\frac{\partial^2 J_{N,m}}{\partial x_{N,m}^2} \geq 0$. Due to $T_{N,m} = \min\{J_{N,m}\}$, it can be easily proved that $\frac{\partial^2 T_{N,m}}{\partial x_{N,m}^2} \geq 0$. Secondly, we assume $\frac{\partial^2 T_{i,j+1}}{\partial x_{i,j+1}^2} \geq 0$, as long as $\frac{\partial^2 T_{i,j}}{\partial x_{i,j}^2}$ can be proved to be non-negative, then we could obtain the proposition 1. According to equation (8), we could get $\frac{\partial^2 J_{i,j}}{\partial x_{i,j}^2} = kf(\theta) + \int_{y=0}^{\infty} \frac{\partial^2 T_{i,j+1}(\theta - y)}{\partial x_{i,j+1}^2} f(y)dy \geq 0$, and then $\frac{\partial^2 T_{i,j}}{\partial x_{i,j}^2} \geq 0$. According equation (5) and duality principle, $T_{i,j}(x,z,v)$ is also convex in z and v.

Proposition 2: Discounted cost $J_{i,j}(x,z,v)$ is convex in $z_{i,j}$ and $v_{i,j}$. There is an unique optimal decision sequence $\{z_{i,j}^*, v_{i,j}^*\}$ that minimizes $J_{i,j}(x,z,v)$, and takes the form as:

$$z_{i,j}^* = \max\{0, \min(z_{i,j}^*, d_i + \Delta\delta(j-m))\} \quad (9)$$

$$v_{i,j}^* = \max\{0, \min(V, Z_{normal} - z_{i,j}^* - x_{i,j} - U\delta(j-\tau))\} \quad (10)$$

Proof: The second order derivative of $J_{i,j}(x,z,v)$ with x has been verified non-negative, that means $\frac{\partial^2 J_{i,j}}{\partial x_{i,j}^2} \geq 0$, and according to the duality principle, $\frac{\partial^2 J_{i,j}}{\partial z_{i,j}^2} \geq 0$ is also non-negative. That means the optimal $z_{i,j}^*$ is the solution of $\frac{\partial J_{i,j}}{\partial z_{i,j}} = c_0 - k + \int_{y=0}^{\infty} T'(\theta - y) f(y)dy = 0$. Considering that $z_{i,j}$ is non-negative, the optimal $z_{i,j}^* = \max\{0, \min(z_{i,j}^*, d_i + \Delta\delta(j-m))\}$. And the optimal $v_{i,j}^*$ could be obtained by "*order up to*" policy by equation (1), so that $v_{i,j}^* = \max\{0, \min(V, Z_{normal} - z_{i,j}^* - x_{i,j} - U\delta(j-\tau))\}$

5 Numerical simulation

Despite the optimal decision sequence $\{z_{i,j}^*, v_{i,j}^*\}$ being proved, no analytical solution could be foreseen in section 4. So in this section, numerical simulation is presented by genetic algorithm, in order to give much more managerial insights by sensitivity analysis to some key parameters. Basic parameters are set as below: electricity demand y in each period during disruption is normal distributed, of which the mean and variance are $\mu = 1$ and $\sigma^2 = 0.1$ respectively. $d_0 = 0.8$, and $d_0 < \mu$. $P(r) = 10^4 r^2$ which means recovery cost is rather expensive and presents characteristic of "*diseconomy of scale*". $k = 100$, $c_0 = 2$, $c_1 = 3$, $c_2 = 4$, $Z_{normal} = 1.65$. Sensitivity analyses on parameters of α, τ, N, m, U and V are assumed to be carried.

5.1 SENSITIVITY ANALYSES ON α

Z_{normal} is the optimal planned capacity of each period, the decision variable $z_{i,j}^*$ should be as close as possible to Z_{normal}, so that the optimal $z_{i,j}^* = d_i + \Delta\delta(j-m)$. Then $\{v_{i,j}^*\}$ can be calculated by equation (10), and $\{v_{i,j}^*\}$ is given in FIGURE 2, where $N = 5$, $m = 5$, $U = 0.2$ and $V = 0.1$. It is quite interesting that the optimal expedite capacity ordering sequence $\{v_{i,j}^*\}$ converges into a rectangular wave with its amplitude equals to V before the 12[th] period when $\alpha \geq 1.0$, while $\{v_{i,j}^*\}$ presents to be a bell-shape curve with its peak decreases when α varies from 0.9 to 0.1. It means that a much more stable and easier decision sequence of $\{v_{i,j}^*\}$ could be obtained when manager takes much more aggressive risk attitude, while the lowest disruption cost is promised when he maximizes the procurement of expedite capacity at the first several disruption periods.

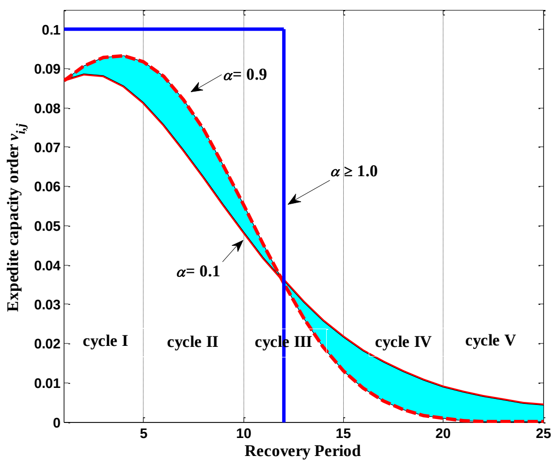

FIGURE 2 Expedite capacity order sequence $\{v_{i,j}^*\}$ when α varies

5.2 SENSITIVITY ANALYSES ON τ, U AND V

Following the parameters setting of section 5.1, the total costs are given by TABLE 1 to show the trends of cost when the lead time of regular capacity τ varies. In generally, total cost would be cut down when τ decreases. However, costs presented in TABLE 1 announce that only 0.13% of cost reduction is contributed when τ decrease from 5 period to 1period. It means that lead time of regular capacity has merely no impact on total cost.

TABLE 1 Total cost when $[\alpha, \tau]$ varies

	τ=2	τ=3	τ=4	τ=5
α=0.1	34829	34841	34852	34874
α=0.5	34813	34832	34836	34848
α=1.0	34808	34823	34839	34855
α=1.5	34808	34823	34839	34855
α=2.0	34808	34823	34839	34855

Furthermore, we would like to investigate whether total costs will be changed when the upper bound of U and V vary. TABLE 2 gives the numerical results when U varies from 0.0 to 0.4 and V varies from 0.0 to 0.3. It is interesting that cost decreases when either U or V increases. However, the increment of U or V has a marginal decreasing effect in cutting down the cost. And even more, costs presented in TABLE 2 announce that only 2.07% of cost reduction in average is contributed when U or V increases. Hereunto, we could draw the conclusion that manager could not have to get more regular and expedite capacity to the best of his ability during the capacity recovery process, because it contributes very small in cutting down the cost. This conclusion also gives the possible implication that manager might not procure any regular or expedite capacity due to the small reduction in cost.

TABLE 2 Total cost when $[U, V]$ vary when $\tau = 2$

	V=0.0	V=0.1	V=0.2	V=0.3
U=0.0	35396	34837	34806	34800
U=0.1	35249	34835	34773	34763
U=0.2	35135	34818	34742	34728
U=0.3	35053	34813	34714	34694
U=0.4	35001	34809	34691	34661

5.3 SENSITIVITY ANALYSES ON N AND m

Further, we would like to investigate the influence of $[N, m]$ on the total cost with $U = 0.4$ and $V = 0.3$. TABLE 3 gives the simulation results. It is interesting that shortening the recovery cycles (N) has nearly no contribution in cutting down the total cost, while cost is greatly cut down by shortening the lead time (m) that recovered capacity is putting into reuse again. Some ways could help to shorten m, such as improving the labour skill of maintenance department; requiring suppliers provide spare parts as soon as possible, seeking the maintenance support from partners, and so on.

TABLE 3 Total cost when [N, m] vary when $\tau = 2$

	m=3	m=4	m=5	m=6	m=7
N=3	20813	27758	34610	41671	48641
N=4	20838	27793	34656	41729	48712
N=5	20867	27833	34661	41795	48795
N=6	20899	27878	34769	41873	48892
N=7	20935	27928	34834	41958	49001

6 Conclusions and future researches

In this paper, a dual capacity sourcing model for an injured power system is presented by investigating the disruption management of SGZEPC in 2008, and correspondingly mathematical proofs are given to verify the existence of optimal decision, and numerical analysis is presented towards several key parameters by genetic algorithm. Three managerial insights are obtained through our research. Firstly, we find that an stable optimal decision sequence in expedite capacity ordering sequence could be obtained when manager takes aggressive risk attitude in recovery process, and the more aggressive the manager is, the more easier for him to make decisions. Secondly, disruption cost could be cut down by shortening the lead time of regular capacity and maximizing the procurement of regular and expedite capacity. However, the reduction in disruption is rather small, which implies that manager could procure none capacity when the procurement coordination cost is relatively high. Thirdly, disruption cost could be greatly cut down when shortening the lead time of recovered capacity being put into reoperation, which implies skilled maintenance labour, fast provision of spare parts and technique support in capacity recovery from partners could do great contribution in cutting down the disruption cost.

Future works will be carried on two respects. First, since the possibility of manager in procuring non capacity, which implies lower service level of power system is during disruption periods. Supervision penalty as well as its optimal boundary should be further verified to prompt manager providing more electricity. Secondly, whether the conclusions mentioned above are still proper when electricity demand is correlated between neighbouring periods should be further researched.

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