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Resilience evaluation framework towards urban power system

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ABSTRACT

As the increased frequency, intensity and duration of extreme weather events have significantly challenged power systems, greater attention has been focused on the development of resilient power systems. Taking a physical-cyber-human system perspective, this paper establishes a multi-criteria resilience evaluation framework for urban power systems, in which two principal elements responsible for power system function degradation are described, and fifteen (eleven objective and four subjective) power system resilience evaluation indicators are identified. Fuzzy hesitant judgement and a TOPSIS aggregation method are applied for the evaluation to minimize expert divergence and maximize group consensus. The evaluation method is then applied to four Chinese municipalities: Shanghai, Beijing and Chongqing, and Tianjin. It was found that Beijing's resilience was the best of the four but overall the urban power system resiliencies were not enough in the face of extreme event challenges.

Keywords: Urban power system, Resilience evaluation, Multi-criteria decision making

1. INTRODUCTION

As the increased frequency of extreme events, such as weather events, accidents, and terrorist attacks [1], has challenged urban power system infrastructure [2], greater attention has been focused on the development of resilient power systems.

A commonly agreed and universally accepted power system resilience definition has not been reached [3], yet it is broadly understood as the ability to withstand high impact-low probability events, rapidly recover from these disruptive events and prevent the impacts of similar future events [1]. However, developing a comprehensive mathematical resilience measure has become a recent research challenge.

Some current power grid resilience assessments emphasize on *how resilient the system is*. For example, Liu et al. [4] calculated the area of "resilience triangle", Panteli et al. [5] proposed "resilience trapezoid" to capture the speed of resilience degradation when adverse events hit the power system. However, although these studies provided valuable information on measuring the resilient power system performances, understanding what specific elements make a system more resilient remains a challenge.

Other studies have proposed attributes-based metrics to assess *what makes the system more resilient*. For example, Abbasi et al. [6] identified resourcefulness, rapid recovery, robustness, and adaptability as the main features of resilient power systems. Dehghanian et al. [7] considered system flexibility, outage costs, and recovery capacity as the core resilience features. However, as an emerging topic, there are still no universally-agreed power system resilience capacity or standardized evaluation metrics.

Therefore, this paper establishes an urban power system resilience evaluation framework from a physical-cyber-human perspective that is focused on the core capacities implied in the widely accepted definitions [1], and proposes evaluation metrics that can be applied by governments and public utilities to evaluate, compare, and enhance power system resilience.

2. POWER SYSTEM RESILIENCE EVALUATION

Power system function degradation results from both external threats and internal risks. External threats are generally related to natural hazards, extreme weather events and terrorist attacks, such as high temperatures, cold waves, heavy rain, strong winds, and cyber attacks; the duration and severity of which

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significantly challenge power system functions [8]. Internal risks are related to the power system's components (generation, transmission and distribution facilities) vulnerabilities [9] and insufficient system operator situational awareness and preparation that results in an inadequate response and system function recovery delays.

This paper considered system wide resilience, which is defined as the joint capacities of the respective power systems to adequately resist to, efficiently coping with, rapidly recover from and properly adapt to external low probability high impact disruptions. This paper evaluates the power system resilience based on these four capacities

2.1 Evaluation framework

To evaluate and compare the strengths and weaknesses of the urban power system resilience, an indicator framework is proposed and the multi-criteria decision-making method is applied.

Eleven objective indicators and four subjective indicators from seven aspects are selected for the power system resilience evaluation, as shown in Fig.1. The preparedness activities and infrastructure resistance reflect the physical domain resistance capacity; the situational awareness and power supply flexibility contribute to the cyber domain coping capacity; and the emergency preparation, support sources, and learning mechanisms contribute to the human domain restoration and adaptability capacities.

2.1.1 Objective indicators

Infrastructure hardening (R_{11}) improves system durability and stability and allows the system to withstand severe events with only minimal damage. The Insulation rate of distribution network (per year) [10] is proposed to assess R_{11}. A is the total urban distribution network length, a_1 is the length of the insulated overhead line, and a_2 is the length of the underground cables.

$$R_{11} = \frac{a_1 + a_2}{A} \times 100\% \quad (1)$$

Vegetation management (R_{12}) has already been incorporated into most power system operations and maintenance activities. Tree-trimming has been the most common and effective vegetation management technique. Ratio of Trimmed Circuits in the most recent three years, as shown in Eq.2, where b is the number of trimmed circuits in the most recent three years, and B is the total circuits

$$R_{12} = \frac{b}{B} \times 100\% \quad (2)$$

Grid connectivity (R_{21}) is related to distribution line topology. This paper applied a Rate of Ring Distribution Network to assess this indicator [10], as shown in Eq.3,

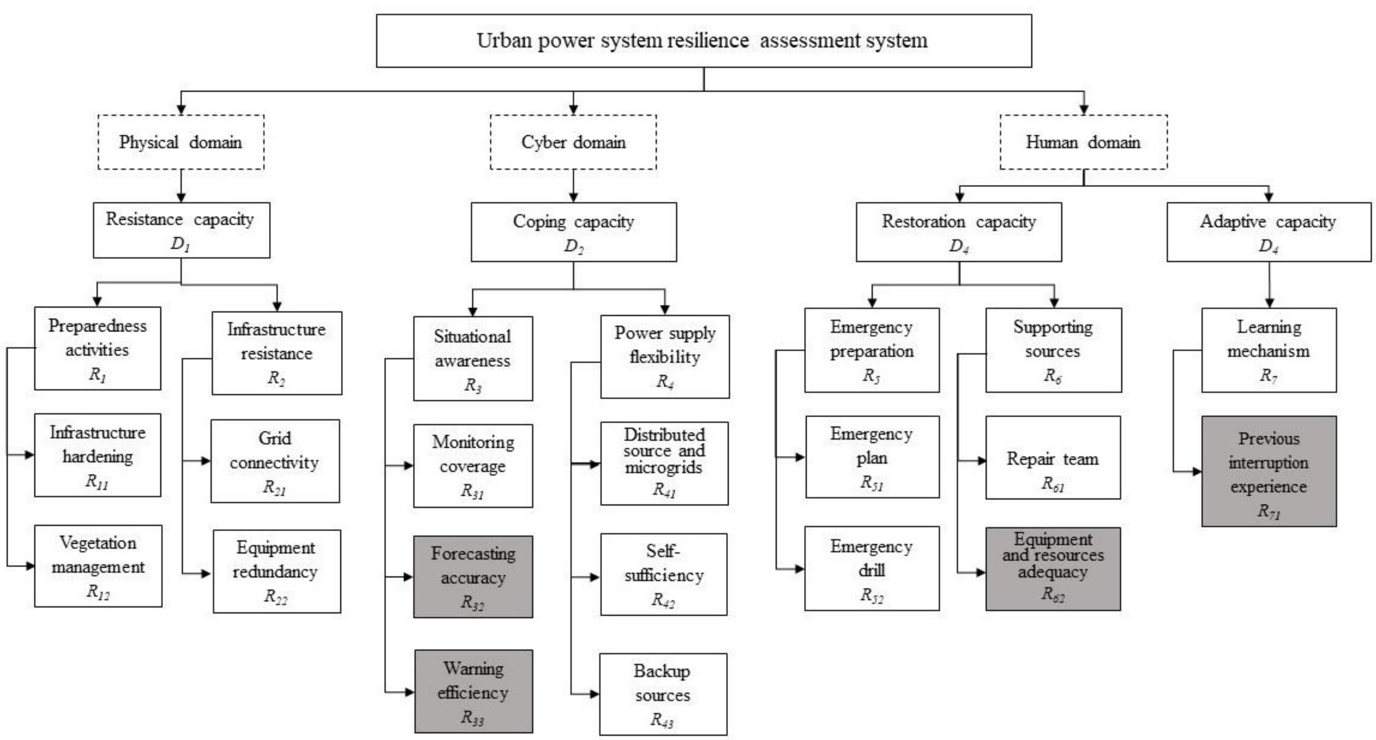

Fig 1 Power resilience evaluation framework

where c is the number of loop network distribution lines, and C is the total number of distribution lines in the urban power grid.

$$R_{21} = \frac{c}{C} \times 100\% \tag{3}$$

Equipment redundancy (R_{22}) refers to the system elements capacities to satisfy the system's functional requirements when there are disruptions, degradation, or a loss of functionality [11]. This paper proposes Reciprocal of Feeder Average Service Length to assess this indicator, as shown in Eq.4, where dn is the length of feeder line n, and d is the average length of the urban feeder lines.

$$R_{22} = \frac{1}{\bar{d}} = \frac{n}{d_1 + d_2 + \cdots d_n} \tag{4}$$

Monitoring coverage (R_{31}) is the basis for situational awareness, which is related to both the regional power grid internal operations status, and the external environmental conditions, such as the meteorological conditions, and external emergencies (the bush/forest fires and earthquakes). The parameter Rate of Automated Distribution Network is selected to assess the internal monitoring coverage (e_1). The external monitoring coverage (e_2) is divided into four levels depending on whether there are mature meteorological information acquisition mechanisms and integration methods in the urban power sector. Each level corresponds to a score, the more mature the information exchange between electric and meteorological departments, the higher the external monitoring score.

$$\mathrm{R}_{31} = e_1 + e_2 \tag{5}$$

Distributed sources (R_{41}), such as on-site wind and PV, provide more sustainable and resilient solutions to the restoration of critical loads [12]. Here the Ratio of the Distributed Power Installed Capacity is used to assess this indicator as shown in Eq.6; where h_j is the installed capacity of the j^{th} distributed generation techniques, and H is the total installed generation capacity.

$$R_{41} = \frac{h_1 + h_2 + \cdots + h_j}{H} \times 100\% \tag{6}$$

Self-sufficiency (R_{42}) is one of the most important policy instruments to ensure energy supply security and sustainability when external disturbances occur[13] . The Self-sufficiency Ratio usually applied to assessing food security [14] is used here to assess this indicator, as shown in Eq.7, where K is the yearly power generation in the studied urban area, k_{ex} is the power exported to other areas, and k_{im} is the power imported from other areas.

$$R_{42} = \frac{K}{K - k_{ex} + k_{im}} \times 100\% \tag{7}$$

Backup sources (R_{43}) are very important for "primary users" such as hospitals, subways, and urban water supplies. To guarantee emergency events power system resilience capacity, these primary consumer demands have to be guaranteed using redundant power supply, stand by power sources, and mobile emergency generators [12] . The Ratio of Primary Users with double (or multiple) Power Supplies (n_1), the Ratio of Primary Users with Stand-by Power Sources (n_2), and the Ratio of Emergency Generation capacity in the Power Supply Station (n_3) are used to assess this indicator, as shown in Eq.8.

$$R_{43} = n_1 + n_2 + n_3 \tag{8}$$

Emergency plans (R_{51}) are the comprehensive and detailed management plans for emergency response. A larger number of emergency plans indicates that the government is better prepared for extreme events; therefore, this indicator is determined from the number of emergency plans, as shown in Eq. 9, where s_1, s_2, and s_3 are the number of comprehensive emergency plans, special emergency plans and on-site disposal plans.

$$R_{51} = s_1 + s_2 + s_3 \tag{9}$$

Emergency drills (R_{52}) are used to test the effectiveness of emergency plans, with the aim of perfecting the emergency preparations, testing the emergency response adaptability, and assessing emergency personnel coordination. The effectiveness of emergency work depends on whether an enterprise has the trained personnel and necessary equipment to deal with the emergency at any time. This indicator is determined by the number of routine drills (l_1) and special drills (l_2) per year, as shown in Eq.10.

$$R_{52} = l_1 + l_2 \tag{10}$$

Repair teams (R_{61}) are a key factor in the restoration period. Professional and efficient emergency repair teams are an important part of system restoration capacity. This indicator is assessed using the available professional construction and emergency repair personnel m_1 and the comprehensive emergency personnel m_2, as shown in Eq.11, where m_1 and m_2 are the power utility repair crews.

$$R_{61} = m_1 + m_2 \tag{11}$$

2.1.2 Subjective indicators

To accurately assign certain values to the forecasting accuracy (R_{32}), warning efficiency (R_{33}), equipment and resources adequacy R_{62}, and previous interruption experience (R_{71}) is very difficult. Therefore, expert evaluation is applied to assess these indicators. As different experts have different opinions regarding power system resilience, they may use different linguistic terms to give their judgements. This paper employed hesitant fuzzy judgements to describe the expert evaluations, for which a symmetric context free 7-scaled grammar linguistic term set (C, shown in Eq.12) is applied to transform the expert evaluations into fuzzy values.

$$\begin{aligned} C &= \{C_{-3}, C_{-2}, C_{-1}, C_0, C_1, C_2, C_3\} \\ &= \{\text{extremelybad}, \text{verybad}, \text{bad}, \text{medium}, \text{good}, \text{verygood}, \text{extremelygood}\} \\ &= \{0, 0.17, 0.33, 0.5, 0.67, 0.83, 1\} \end{aligned} \tag{12}$$

For example, $K_C^1 = \{C_0\} = \{0.5\}$, $K_C^2 = \{C_{-2}, C_{-1}\} = \{0.17, 0.33\}$, $K_C^3 = \{C_0, C_1, C_2\} = \{0.5, 0.67, 0.83\}$, and $K_C^4 = \{C_{-1}, C_0, C_1, C_2\} = \{0.33, 0.5, 0.67, 0.83\}$ .As the number of values for different elements in K_C^x may be different, it is necessary to extend the shorter element until all elements have the same length (L) so that the distance and similarity can be compared. Therefore, we introduce evaluator's altitude parameter $\mu (0 \le \mu \le 1)$, then the extension value is $\bar{\kappa} = \mu\kappa^+ + (1-\mu)\kappa^-$, where $\kappa^+$and κ^- are the maximum and minimum values in K_C^x [15].

2.1.3 Experts Weight Determination

Determining the expert weights in group decision-making problems is complex and difficult [16]. Previous studies tend to give equal weights or fuzzy weights [17]. To minimize the divergency in the expert evaluations and maximize the group evaluation consensus, this paper uses Euclidean-distance-based model to minimize the sum of hesitant fuzzy rating distances between two experts to determine experts' weights.

$$\min_{\omega_k} D = \sum_{i=1}^{I} \sum_{j \in J_H} \sqrt{(1/L) \sum_{l=1}^{L} \sum_{p=1}^{K} \sum_{q=1}^{K} \left(\omega_p h_{ijp}^l - \omega_q h_{ijq}^l\right)^2} + \sum_{j=1}^{J} \sqrt{(1/T) \sum_{t=1}^{T} \sum_{p=1}^{K} \sum_{q=1}^{K} \left(\omega_p g_{jp}^t - \omega_q g_{jq}^t\right)^2}$$

$$s.t. \begin{cases} h_{ijp} = \{h_{ijk}^l \mid l \in L, i \in I, j \in J_H, p \in K\} \\ h_{ijq} = \{h_{ijk}^l \mid l \in L, i \in I, j \in J_H, q \in K, q \ne p\} \\ g_{jp} = \{g_{jk}^t \mid t \in T, j \in J, p \in K\} \\ g_{jq} = \{g_{jk}^t \mid t \in T, j \in J, q \in K, q \ne p\} \\ \sum_{k=1}^{K} \omega_k = 1, \omega_k \ge 0 \end{cases} \tag{13}$$

$$\bar{h}_{ijk} = \{\omega_k h_{ijk}^l \mid l \in L, i \in I, j \in J_H, k \in K\}$$

$$\bar{g}_{jk} = \{\omega_k g_{jk}^t \mid t \in T, j \in J, k \in K\}$$

2.1.4 Criteria Weight Determination

Similar to subjective evaluation, indicator importance of this paper is also judged by the experts using context-free grammar judgements. To compute indicator weights, a weighted averaging operator is developed, as shown in follows.

$$\begin{cases} \alpha_j = \sum_k \bar{g}_{jk}^{\ 1} \\ \beta_j = \sum_k \frac{1}{T-2} \left(\bar{g}_{jk}^{\ 2} + \bar{g}_{jk}^{\ 3} + \cdots + \bar{g}_{jk}^{\ T-1}\right) \\ \pi_j = \sum_k \bar{g}_{jk}^{\ T} \end{cases} \tag{14}$$

By using the intuitionistic fuzzy weighted averaging operator proposed by Xu [18], the weight of the j^th^ indicator can be obtained, as shown in Eq.15.

$$\varpi_j = \frac{\alpha_j + \pi_j \left(\frac{\alpha_j}{\alpha_j + \beta_j}\right)}{\sum_{j=1}^{J} \left[\alpha_j + \pi_j \left(\frac{\alpha_j}{\alpha_j + \beta_j}\right)\right]} \tag{15}$$

2.1.5 TOPSIS Aggregation Method

Given a set of criteria, expert's weights and criteria weights, the next task is to aggregate the evaluation results from different experts into an integrated group consensus. For the subjective evaluation criteria $j \in J_H$, let $x_{ij}^l = \sum_k \omega_k h_{ijk}^l \,(l \in L, k \in K, j \in J_H)$ represents the experts' evaluation results of criteria j for urban power system i, in which h_{ijk}^l is obtained by expert interview, and ω_k is obtained by Eq.13. For the objective evaluation criteria ($j \in J_C$), the indicator values $x_{ij}\,(j \in J_C)$ are obtained from data collection. Therefore, the urban power system resilience evaluation matrix can be expressed as follows.

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1J} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iJ} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{I1} & \cdots & x_{Ij} & \cdots & x_{IJ} \end{bmatrix} \tag{16}$$

To calculate the normalized and weighted matrix P, we let $f_{ij}, j \in J_C$ and $f_{ij}, j \in J_H$ denotes to the vector normalization for indicator J_C and J_H, where

$$\begin{aligned} f_{ij} &= \frac{x_{ij}}{\sqrt{\sum x_{ij}^{\ 2}}} \mid i \in I, j \in J_C \\ f_{ij}^{\ l} &= \left(\frac{x_{kj}^{\ l}}{\sqrt{\sum x_{ij}^{\ l\,2}}} \mid l \in L\right), i \in I, j \in J_H \end{aligned} \tag{17}$$

Using the weighted averaging operator in Eq.15, criteria weight can be obtained. Therefore, the normalized and weighted decision matrix P is obtained. TOPSIS method takes advantage of the positive-ideal solution and the negative-ideal solution in the multi-criteria problems. Therefore, the next step is to determine the power system that have the most P^+

and least P^- preferable power system resilience, using the following rules.

$$P^+ = \left\{ \max_i \left(p_{ij} \right) | j \in J \right\} = \left\{ p_1^+, \ldots, p_j^{l+}, \ldots, p_J^+ \right\}$$
$$P^- = \left\{ \min_i \left(p_{ij} \right) | j \in J \right\} = \left\{ p_1^-, \ldots, p_j^{l-}, \ldots, p_J^- \right\} \quad (18)$$

Next step is to calculated the Euclidean distance between each urban power system and the system with the most/least preferable resilience.

$$S_i^+ = \sqrt{\sum_{j \in J_C} \left(p_{ij} - p_j^+ \right)^2 + \frac{1}{L} \sum_{j \in J_H} \sum_L \left(p_{ij} - p_j^{l+} \right)^2}$$
$$S_i^- = \sqrt{\sum_{j \in J_C} \left(p_{ij} - p_j^- \right)^2 + \frac{1}{L} \sum_{j \in J_H} \sum_L \left(p_{ij} - p_j^{l-} \right)^2} \quad (19)$$

The last step is to calculate he relative closeness of each city's power system resilience to the most preferable one P^+, as shown in the following. Then by ordering V_i^+ in descending order, the urban power system's resilience can be ranked from the best to the worst.

$$V_i^+ = \frac{S_i^-}{S_i^- + S_i^+}, 0 < V_i^+ < 1 \quad (20)$$

3. CASE STUDY

The four municipalities in China; Shanghai, Beijing, Tianjin and Chongqing are selected to illustrate the function and performance of the proposed urban power resilience assessment framework. Results shown in Fig 2.

From Fig. 2, it can be seen that Beijing had the highest restore capacity at 0.156, Tianjin had the highest coping capacity at 0.203, and Shanghai had the highest resist capacity at 0.136. Therefore, Beijing's power system resilience strengths was human adaptability, Tianjin's was its cyber coping ability, and Shanghai was its physical resistance. However, Chongqing only had a physical resistance capacity of 0.101, which were inferior to the other three municipalities.

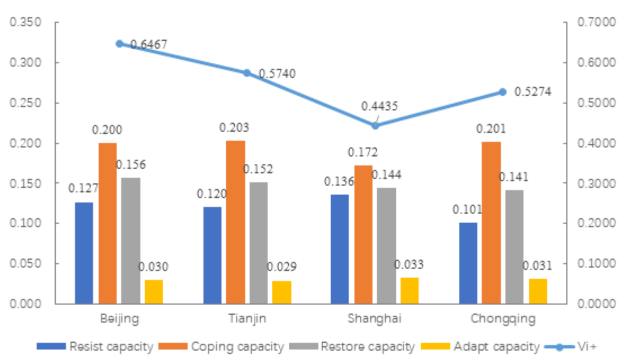

Fig 2 Capacity score and V_i^+ value of the four cities

The TOPSIS-based aggregation method described in Section 3.1.2, was then applied to the power system resilience evaluation results for Beijing, Tianjin, Shanghai and Chongqing, with the results respectively being V_i^+ =0.6467, 0.5740, 0.4435, and 0.5274. Therefore, Beijing's power system resilience ranked first, followed by Tianjin, Chongqing and Shanghai. When the value of V_i^+ is between 0 and 0.2, the urban power system is deemed highly non-resilient, when the value is between 0.2 and 0.4, it is non-resilient, when the value is between 0.4 and 0.6, it is relatively resilient, when the value is between 0.6 and 0.8, it is resilient, and when the value is between 0.8 and 1, it is highly resilient. Therefore, the urban power systems in Beijing was found to be resilient, and Tianjin, and Shanghai Chongqing were relatively resilient.

4. CONCLUSION

This paper proposed an urban power system resilience evaluation framework from the physical-cyber-human perspective and established a quantitative resilience evaluation method based on multi-criteria decision making. Two principal elements that lead to power system performance degradation were described, and eleven objective and four subjective resilience evaluation indicators were identified. As accurately evaluating subjective indicators is difficult, expert evaluation was applied to assess these indicators and their relative importance, and a TOPSIS aggregation method was used to achieve group evaluation consensus maximization. A case study in four Chinese municipalities was given to illustrate the functions and performances of the evaluation framework, the calculation results for which ranked the cities' resilience score and identified their respective strengths and weaknesses. None of the four municipalities were found to have very strong urban power system resilience and all required significant changes to be fully prepared for extreme weather events.

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