IET Generation, Transmission & Distribution

Research Article

IET Journals
The Institution of Engineering and Technology

Identification of critical lines for enhancing disaster resilience of power systems with renewables based on complex network theory

ISSN 1751-8687
Received on 10th December 2019
Revised 27th May 2020
Accepted on 29th June 2020
E-First on 3rd September 2020
doi: 10.1049/iet-gtd.2019.1853
www.ietdl.org

Yuxuan Zhao[1], Shengyuan Liu[1], Zhenzhi Lin[1,2] ✉, Li Yang[1], Qiang Gao[3], Yiwei Chen[3]

[1]*College of Electrical Engineering, Zhejiang University, Hangzhou 310027, People's Republic of China*
[2]*School of Electrical Engineering, Shandong University, Jinan 250000, People's Republic of China*
[3]*State Grid Zhejiang Taizhou Electric Power Supply Company, Taizhou 318000, People's Republic of China*
✉ *E-mail: linzhenzhi@zju.edu.cn*

Abstract: Natural disasters, such as typhoons and earthquakes, pose great challenges to power system resilience and power supply reliability. It is widely acknowledged that critical transmission lines play a significant role in enhancing the resilience and reliability of power systems under severe natural disasters. In order to improve the disaster resilience of power systems with renewables, a critical line identification approach is proposed in this work based on the complex network theory. Firstly, the concept of core skeleton network (CSN) of power systems with renewables is introduced and a two-step strategy is presented to optimise the CSNs of the concerned power system considering the variable outputs of renewables. Then, a statistical salience method incorporating edge salience and the state-of-the-art null model in complex network theory is proposed to identify critical lines of each CSN and the concerned power system with renewables. Finally, the effectiveness of the proposed critical lines identification approach is verified by simulations on the modified IEEE 118-bus system with renewables, Guangdong Provincial Power System (GPPS) and Zhejiang Provincial Power System (ZPPS) in China. Simulation results show that by using the proposed approach, the critical transmission lines can be effectively identified, not requiring a predefined number of critical lines.

Nomenclature

Indexes and sets

(i, j)	index of the transmission line between node i and node j
o/s	index of original/typical scenario
k/p	index of load/power source node
t	index of hour
G_0	original power network, $G_0 = (V,\ E)$, where V and E represent the node set and line set of the original power network, respectively
$G_1(s)$	connected sub-network of G_0 in scenario s, which contains all the critical load nodes and part of lines
$G_2(s)$	CSN of G_0 in scenario s
O/R	set of original/typical scenario
Ω_{L}	set of load nodes in G_0
Ω_{WF}^s	set of WF nodes in $G_2(s)$
Ω_{LF}^s	set of load nodes in $G_2(s)$
Ω_{PF}^s	set of PV nodes in $G_2(s)$
Ω_{CF}^s	set of CPP nodes in $G_2(s)$

Parameters

$D_{ij,s}^{\mathrm{d}}$	effective length from node j to node i for scenario s
$D_{ij,s}$	effective distance between any node pair $\langle j,\ i\rangle$ for scenario s
$I_C[\cdot]$	indicator function
K	maximum size of R
F_{ij}^s	specific 'flow' from node j to node i for scenario s
$P_{ps}^{\mathrm{W}}(t)$	output power of the pth WF at time t in scenario s
$P_{ps}^{\mathrm{P}}(t)$	output power of the pth PV at time t in scenario s
$P_{ks}^{\mathrm{L}}(t)$	load power of load node k at time t in scenario s
$P_{\mathrm{R}}(t)$	load reserve capacity of $G_2(s)$ at time t
P_p^{CN}	rated output power of the pth CPP
P_p^{Cm}	minimum output power of the pth CPP
P_p^{WN}	rated output power of the pth WF
P_p^{PN}	rated output power of the pth PV
$S_{ij}^s(t)$	power flow of transmission line (i, j) at time t in scenario s
$S_{ij}^{\max}$	capacity of transmission line (i, j)
$\boldsymbol{\omega}_{os}$	similarity matrix for scenario pair o and s
λ	parameter for controlling similarity scaling
$\boldsymbol{s}_o/\boldsymbol{s}_s$	vector representing the value of scenario o/s
l_{ks}^{L}	relative importance of load node k in scenario s
l_{ps}^{S}	relative importance of power source node p in scenario s
$l_{p-G_1(s)}$	number of transmission lines between power source node p and $G_1(s)$
x_{ij}	reactance of line (i, j)
θ_1	coefficient for the first-step CSN optimisation problem
θ_2	coefficient for the second-step CSN optimisation problem
$\gamma_{\mathrm{W}}^s\%$	penetration limit of wind power injected into $G_2(s)$
$\gamma_{\mathrm{P}}^s\%$	penetration limit of solar power injected into $G_2(s)$
$\gamma_{\mathrm{W_0}}\%$	penetration limit of wind power injected into G_0
$\gamma_{\mathrm{P_0}}\%$	penetration limit of solar power injected into G_0
N_s^{G}	number of power source nodes in $G_2(s)$
N_s^{L}	number of load nodes in $G_2(s)$
$g_{ik}^{(i,j)}$	times that the shortest paths from the node i to the load node k pass through line (i, j)
g_{ik}	number of shortest paths from node i to the load node k
e_{ij}^s	line salience, or ES, of line (i, j) for $G_2(s)$
J_{ij}^s	statistical salience of line (i, j) for $G_2(s)$
k_i	degree of node i
$f(x, k_i)$	probability density function of the line salience of node i considering its degree k_i

Variables

λ_1^s/λ_2^s	objective of the first/second step CSN optimisation model

a_{ij}^s binary variable; equal to 1 if line (i, j) is in $G_1(s)$, and 0 otherwise

b_{ks} binary variable; equal to 0 if node k is in $G_1(s)$, and 1 otherwise

v_{ps} binary variable; equal to 1 if power source node p is in $G_2(s)$, and 0 otherwise

1 Introduction

Natural disasters, such as typhoons, ice and snow, and earthquakes, pose great challenges to power system operations, heavily undermine power system resilience and power supply reliability and even result in outages or blackouts under extreme conditions [1, 2]. For example, a heavy ice and snow disaster attacked South China in 2008 and resulted in outage of more than 100 substations and 500 transmission lines, and damage of more than 2000 transmission towers [3]. From 2016 to 2018, several typhoons attacked Guangdong Provincial Power System (GPPS) in China, and each of them caused outage of millions of households. So far, many researches are conducted to enhance the disaster resilience of power systems. For example, in [4], an operational resilience assessment approach is proposed for power system considering the effect of the extreme weather and the real-time loading condition. In [5], a resilience evaluation approach using the sequential Monte Carlo simulation and a risk-based defensive islanding approach are presented to enhance the power system resilience under extreme weather events. In [6], with application to the impact modelling of severe windstorms on the transmission network, a comprehensive approach is presented to assess and enhance the transmission system resilience under extreme weather conditions. In [7], a mathematical framework for determining the resilient network investments is presented. The proposed framework in [7] can hedge the risks caused by natural disasters and can be applied to various natural disasters. In order to assess and enhance the disaster resilience of power systems, the concept of the fragility curve of a specific power system component is presented and applied in [4–7].

In terms of enhancing the disaster resilience of power systems, it is widely acknowledged that reinforcing some critical transmission lines and keeping them operating as reliably and uninterruptedly as possible under severe natural disasters or, if outage is unavoidable, restoring them immediately after the disasters, are crucial for enhancing the disaster resilience of power systems [1, 8–10]. Therefore, it is of practical significance to identify and then reinforce the critical transmission lines so as to not only improve the power system resilience and power supply reliability under severe natural disasters but also facilitate the restoration process if an outage occurs. With respect to the critical lines identification, most of the existing publications are based on the complex network theory. In [10], with edge betweenness and electrical node significance adopted as criticality index, the hypothesised multiple line attacks are carried out to identify critical lines. In [11], based on electrical betweenness entropy, a critical line identification model considering topology structure and power flow distribution of power systems is proposed and formulated as a mixed-integer non-linear programming model. In [12], an extended topological approach incorporating flow paths, line flow limits and generator/load distribution, and a global metric 'survivability' assessing the aptitude of a network to withstand natural failures or malicious attacks, are proposed to identify critical components including transmission lines that need to be reinforced. In [13], a coupling strength index capable of identifying critical nodes and lines is presented based on inherent structural characteristics theory and atomic theory. In [14], an extended topological approach of three metrics, i.e. entropy degree, electrical betweenness and net-ability, is presented to evaluate the critical buses and branches in power systems. In [15], the vulnerable transmission lines are identified through defining the hybrid flow betweenness that incorporates power flow directions, transmission capacity limits and electrical coupling degree. In [16], vulnerable transmission lines are recognised by the improved structural hole theory which takes into account the interaction between nodes and reflects the correlations between lines. In [17], a two-step max-flow based method is presented to identify critical lines, where the first step models the power network as a graph and then principal component analysis and convex hull are used to extract critical scenarios, and the second step utilises an improved max-flow approach for topology analysis.

Although many research works have been conducted to identify critical transmission lines for improving the power system resilience and power supply reliability under severe natural disasters and extreme operation conditions, two issues still remain to be dealt with. On the one hand, since the critical lines are decided from the evaluated ranking order of line importance, a predefined number of critical lines is required in the above research works to determine which lines are critical. However, it is difficult for the decision makers to decide an appropriate number either before or after evaluation of ranking order. An inappropriate number may result in that critical lines are categorised as non-critical or non-critical lines as critical, thus the resilience and reliability of the concerned power system cannot be effectively improved. On the other hand, with the increasing penetration of renewable energy sources (RESs) into power systems, the traditional methods (referring to transmission line identification methods presented for traditional power system without variable renewables) may not be applicable to power systems with RESs, such as wind power and solar power. For one aspect, the variability nature of renewables such as wind power and solar power poses significant challenges to critical line identification, while the traditional methods may not tackle the variable output of RESs appropriately. For another aspect, the traditional critical line identification methods tend to regard every power source equally, and even power source nodes and load nodes equally, thus are incapable to handle various power source nodes in power systems with RESs when determining the critical lines.

To address the above issues, this work proposes a statistical salience method to identify critical lines for power systems with RESs, such as wind farms (WFs) and photovoltaics (PVs), based on complex network theory. To derive the statistical salience method, the concept of core skeleton network (CSN) is introduced and a two-step strategy is proposed for optimising CSN for power systems with RESs. Since the power outputs of RESs vary with weather conditions and seasons, the CSN is optimised for each typical operational scenario of RESs in the concerned power system. In the strategy, the relative importance of various types of nodes, such as load nodes, WF nodes, PV nodes and conventional power plant (CPP) nodes, in power networks is evaluated for each typical scenario, and the nodes with larger relative importance are reserved into the CSN for the concerned typical scenario. The first step of the two-step strategy aims to optimise a connected sub-network containing all the critical loads, while the second step aims to optimise the CSN that contains important power sources including RESs. Based on the attained CSNs, the statistical salience methodology is proposed to identify critical lines for each CSN and finally the concerned power system. With the edge salience (ES) and the null model (NM) of complex network theory incorporated, the proposed statistical salience method makes a null hypothesis and thus can identify critical lines for power systems with RESs through a significance level showing how satisfied the null hypothesis could be. Compared with the existing publications that generally require a pre-specified number of critical lines [10–17], the proposed statistical salience can clearly identify the transmission lines as critical ones and non-critical ones without the need of specifying the number of critical lines.

To the best of the authors' knowledge, it is the first time that the critical lines identification strategies for power systems with RESs are presented, which is of practical significance as power systems are accommodating increasing penetration of RESs worldwide. The main contributions of this work are as follows: (i) a critical lines identification approach for enhancing the disaster resilience of power system with RESs is proposed for the first time, by which the lines can be clearly classified into critical lines and non-critical lines, not requiring a predefined number of critical lines; (ii) a two-step CSN optimisation strategy for power systems with RESs is presented, by which the loads and power sources including WFs and PVs can be reasonably arranged and thus the power system

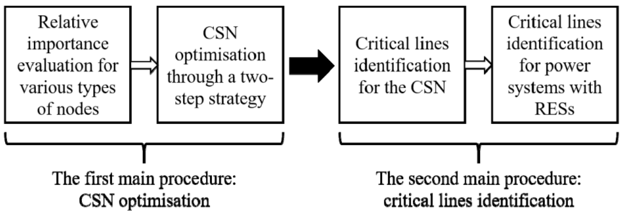


Fig. 1 *Illustration of the proposed critical lines identification approach*

resilience and power supply reliability effectively improved for each typical scenario under severe natural disasters; (iii) the variabilities of the output power of RESs, such as WFs and PVs, are considered in the CSN optimisation and critical lines identification problems; (iv) load nodes and various power source nodes in power systems with RESs are treated differently and evaluated individually via multiple indexes that capture the typological and electrical characteristics.

The rest of this work is organised as follows. The architecture of the proposed critical line identification approach is described in Section 2. The concept of CSN and the two-step CSN optimisation model is presented in Section 3. Section 4 proposes the statistical salience method for critical lines identification. Case studies on the modified IEEE 118-bus system with RESs, GPPS and Zhejiang Provincial Power System (ZPPS) in China are performed on Section 5. This work is concluded in Section 6.

2 Architecture and typical scenarios of the proposed critical line identification approach

2.1 Architecture of the proposed critical line identification approach

In this work, a critical line identification approach based on the statistical salience method of the complex network theory is proposed for enhancing the disaster resilience of power systems with RESs (such as WFs and PVs). The intermittent nature of RESs is considered through typical scenarios. The proposed approach consists of two main procedures. The first procedure aims to determine a CSN for the power system with RESs. For each typical scenario, the relative importance of various types of nodes in the concerned power network is evaluated, and the nodes with larger relative importance may be reserved in the CSN. The optimal CSN that consists of some transmission lines and nodes with larger relative importance can be determined through a two-step strategy, where the first step optimises the load nodes and constructs a connected sub-network, while the second step optimises the power source nodes and determines the CSN. The second procedure aims to identify critical lines utilising the statistical salience method of the complex network theory. For each CSN, some critical lines can be identified. Finally, the critical lines for the concerned power system with RESs can be determined based on each CSN's critical lines. The architecture of the proposed critical line identification approach is illustrated in Fig. 1.

2.2 Typical scenarios of power systems with RESs

In power systems with renewables, the output power of RESs fluctuates with weather and season and each RES has its own generation characteristic different with others, which leads to a substantial number of various scenarios in the concerned power system. One scenario matches one optimal CSN and the final results of the critical lines depend heavily on the scenarios and the CSNs optimised. However, including a substantial number of scenarios into the critical lines identification model will result in significant challenge to computations. To reduce the computational burden and make the CSN optimisation and critical line identification models tractable, some typical and representative scenarios that capture most of the possible situations should be selected from the original scenario set [18]. The original scenarios can be attained from historical data or statistical models of the concerned power system, which is not focused in this work.

With respect to extracting typical scenarios, there are many approaches, such as fast forward selection and the *k*-means method [19], which can effectively reduce the original set with a large number of scenarios to a smaller subset with a small number of typical and representative scenarios. However, these techniques are less efficient and unable to handle a large original set with scenarios, compared with the cardinality constrained submodularity based scenario reduction (CCSBSR) technique [20]. Based on submodular function optimisation theory, CCSBSR can achieve orders of magnitude performance speedups and tackle a very large original set, and has been widely utilised in power system decision-making problems recently. In this work, the CCSBSR method is utilised to attain typical scenarios, the CCSBSR method can be formulated as follows [20]:

$$\max_{R} f(R) = \max_{R} \left(\sum_{o \in O} \max_{s \in R} \omega_{os} \right) \tag{1}$$

$$\text{s.t.}: |R| \le K \tag{2}$$

$$\omega_{os} = \exp\left(-\frac{\| \boldsymbol{s}_o - \boldsymbol{s}_s \|_2}{\lambda} \right) \tag{3}$$

where $\| \cdot \|_2$ represents the second-order norm and $|R|$ represents the cardinality of set R. K is maximum size of set R. A resolution of 24 h (one day) is adopted for each scenario in this work. Since the output power of each RES also depends on its installed capacity, the output power of each RES in the operational scenarios is normalised using the installed capacity before scenario generation and reduction.

3 Two-step CSN optimisation strategy

3.1 CSN for power systems with renewables

The CSN for a power system can be deemed as a connected sub-network containing some critical components that are indispensable for the power system to keep survivability under severe natural disasters and extreme operation conditions. The operational characteristics of various WFs and PVs should be fully considered when optimising CSN in power systems with renewables. In this work, the variabilities of RESs are modelled as scenarios, which is discussed in Section 2.2. In addition, the penetration limits of wind power and solar power should be taken into account in the optimisation of CSN. The wind (solar) power penetration limit of a specific power system is defined as the ratio of the maximum wind (solar) power capacity (that the power system can accommodate) to the maximum load of this system [21, 22]. Evaluations of the power penetration limits have been investigated in many publications, thus are not discussed [23, 24]. The wind power and the solar power integrated into the CSN should be within their corresponding penetration limits, respectively. Thus, the characteristics of CSN in power systems with renewables can be summarised as follows:

(i) the power supply to critical loads should be uninterruptible;
(ii) the topological configuration of the optimised CSN should be reasonable and topologically connected;
(iii) the operation and security constraints to the CSN should be respected;
(iv) the penetration and utilisation of RESs in the CSN should be as high as possible if the requirements of (i) to (iii) are met;
(v) the number of the transmission lines in the CSN should be as small as possible if the requirements of (i) to (iv) are met.

On no conditions should the power supply to critical loads be interrupted in the CSN, as required by (i) to (iii). If the power supply to critical loads of the optimised sub-network, or CSN, is guaranteed, it could be economically and environmentally beneficial for the power system to accommodate as high penetration of RESs such as WFs and PVs as possible. That is because the generating costs of WFs and PVs are generally much

Table 1 Indexes utilised for evaluating the relative importance of various nodes

	Topological indexes	Electrical indexes
load nodes	degree-clustering coefficient [25]	energy consumption, power flow flux
WF nodes	effective distance based closeness centrality [26, 27]	equivalent utilisation hours, average wind speed, energy storage deployment
PV nodes	effective distance based closeness centrality [26, 27]	equivalent utilisation hours, performance ratio [28]
TPP nodes	effective distance based closeness centrality [26, 27]	maximum spinning reserve capacity, ramping rate

less than those of the conventional thermal power plants (TPPs) and more and more RESs are being accommodated in power systems so as to mitigate greenhouse gas emissions and deal with fossil energy crisis. Although the CSN can withstand disasters and improve survivability of the concerned power system under severe natural disasters and extreme operation conditions, the power system is still at the risk of an outage on some conditions. However, incorporation of RESs such as WFs and PVs into the CSN can not only increase the economic and environmental benefits but it can also facilitate the restoration processes after an outage or a blackout [8]. Furthermore, in order to increase the economic benefits, the number of the transmission lines contained in the CSN should be as small as possible so as to reduce investments in reinforcing and enhancing transmission infrastructure, as required by (v).

Based on these characteristics, the two-step CSN optimisation strategy and the statistical salience methodology for critical lines identification are presented as follows.

3.2 Relative importance evaluation of various types of nodes

In essence, the optimisation of CSN is to find an optimal connected sub-network that consists of all the critical load nodes, part of power source nodes and some transmission lines. The traditional CSN optimisation strategies usually tend to deem the load nodes and power source nodes identically, and overlook the difference between different types of nodes. Both the load nodes and the power source nodes are regarded as one type of nodes in most of the existing publications [10–13, 15, 16], however, their injected power direction and relative importance are different. In addition, different types of power sources have various electrical characteristics and parameters. If the load nodes and power source nodes are handled indiscriminately or various types of power source nodes regarded identically, critical lines may not be effectively identified and reserved in the CSN, and the resilience of the concerned power system under severe natural disasters or extreme operation conditions may not be enhanced. Therefore, load nodes and each type of power source nodes in the power system with RESs should be evaluated and ranked individually so as to optimise the CSN. The power source nodes in power systems with renewables generally consist of WF nodes, PV nodes and CPP nodes including hydro-electric plant (HEP) nodes and TPP nodes. Since different types of nodes have different topological and operating characteristics, various evaluation indexes should be used, respectively, for each type of nodes based on complex network theory and electrical characteristics of power systems. However, selection of the evaluation indexes is not the focus of this work, and only the CSN optimisation and critical line identification are addressed. The used relative importance evaluation indexes for loads nodes and power source nodes are shown in Table 1.

The effective distance based closeness centrality is used as a topological index to evaluate the relative importance of power source nodes [26, 27]. Since the effective distance is also a significant component for identifying critical lines in Section 4.2, it is presented as follows [26]. For any transmission line (i, j), the effective length from node j to node i for scenarios s can be expressed as

$$D^{\mathrm{d}}_{ij,s} = 1 - \ln\left(F^s_{ij} / \sum_{j \prec i} F^s_{ij}\right) \tag{4}$$

where $j \prec i$ represents that node j is the neighbour of node i. F^s_{ij} represents the 'flow' from node j to node i, and in this work it is computed by incorporating the load node importance, as

$$F^s_{ij} = \begin{cases} l^{\mathrm{L}}_{is} l^{\mathrm{L}}_{js} x^{-1}_{ij} & \text{if } i, j \in \Omega_{\mathrm{L}} \\ l^{\mathrm{L}}_{is} x^{-1}_{ij} & \text{if } i \in \Omega_{\mathrm{L}}, j \notin \Omega_{\mathrm{L}} \\ l^{\mathrm{L}}_{js} x^{-1}_{ij} & \text{if } i \notin \Omega_{\mathrm{L}}, j \in \Omega_{\mathrm{L}} \end{cases} \tag{5}$$

where l^{L}_{is} is the evaluated relative importance of load node i. Based on effective length, the effective distance between any node pair $\langle j, i \rangle$ for scenarios s can be defined as

$$D_{ij,s} = \min \sum_{h \in H} (D^{\mathrm{d}}_{ih,s} + \cdots + D^{\mathrm{d}}_{hj,s}) \tag{6}$$

where h represents the intermediary nodes connecting node j and node i. H is the set of nodes in the paths from nodes j to i.

Based on the effective distance (6), the effective distance based closeness centrality can be attained accordingly [27], and the shortest path in (19) determined. Note that the critical load nodes are generally prescribed by the power system operator according to the power supply requirement and load type. On this condition, all the prescribed critical load nodes should be reserved into the CSN, and their evaluated relative importance could be used to evaluate the relative importance of power source nodes. The TPPs are reserved into the CSN based on the evaluated relative importance, whereas all HEPs are kept into the CSN as they are the main resources for peak load regulation and frequency regulation and act as black start resources after a blackout of the power system. The entropy weight and TOPSIS method [29] is used to evaluate the relative importance of load nodes, WF nodes, PV nodes and TPP nodes. Then, based on the relative importance of various types of nodes, the two-step CSN optimisation strategy can be implemented.

3.3 Two-step CSN optimisation strategy

As mentioned, a two-step CSN optimisation strategy is proposed first, based on which critical lines can be identified.

3.3.1 First step: optimisation of load nodes for the CSN: The CSN optimisation model in the first step is to find a connected sub-network (denoted as G_1) with critical load nodes and part of lines based on the original power network (denoted as $G_0 = (V, E)$, where V and E represent the node set and edge, or line, set of the power network, respectively). In order to attain a reasonable connected sub-network with as few lines as possible, the objective of the first step model is to minimise the number of transmission lines and maximise the relative importance of load nodes in the connected sub-network G_1. Since maximising the importance of the load nodes within G_1 is equivalent to minimising of the importance of the load nodes outside G_1, the CSN optimisation model in the first step for scenario $s \in R$, where R is a set of typical scenarios, can be expressed as

$$\min \lambda^s_1 = \sum_{(i,j) \in E} a^s_{ij} + \theta_1 \sum_{k \in \Omega_{\mathrm{L}} \subseteq V} b_{ks} l^{\mathrm{L}}_{ks} + I_{\mathrm{C}}[G_1(s)] \tag{7}$$

If the critical load nodes are prescribed by the decision maker, their corresponding b_s can be set as 0. θ_1 is a coefficient for addressing the dimensional problems and compromising between the overall relative importance of nodes and the number of lines. $I_{\mathrm{C}}[\cdot]$

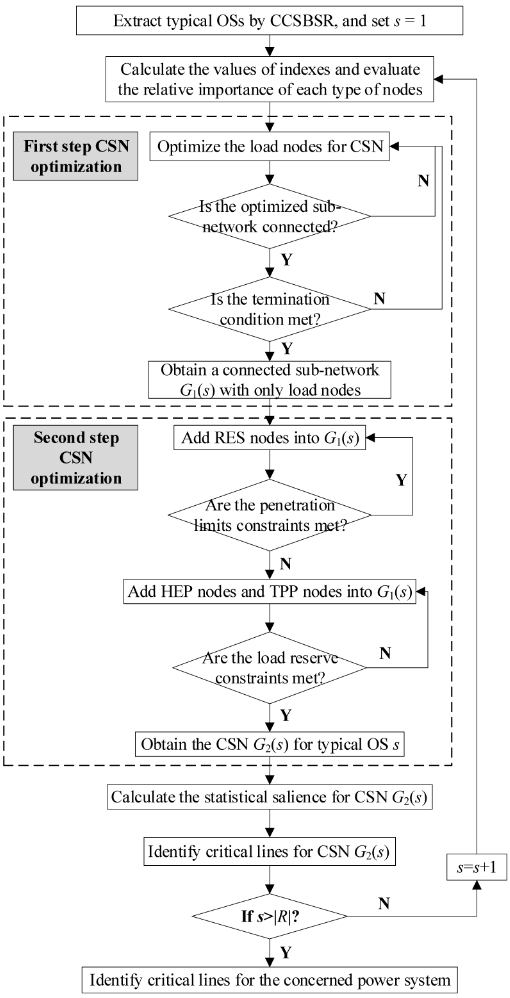


Fig. 2 *Flow chart of the proposed critical line identification approach*

constrains the connectivity of the optimised sub-network $G_1(s)$, and $I_C[G_1(s)] = 0$ if $G_1(s)$ is connected; otherwise $I_C[G_1(s)] = +\infty$.

3.3.2 Second step: optimisation of power source nodes for the CSN: The CSN optimisation model in the second step aims at optimising power source nodes. After $G_1(s)$ is obtained, some power source nodes and lines should be integrated into $G_1(s)$ according to the relative importance ranking of nodes so as to provide the critical loads with electric energy, and then the CSN $G_2(s)$ for scenarios s can be attained. The objective of the second step model is to maximise the overall importance of power source nodes and to minimise the number of all transmission lines between the power source nodes and $G_1(s)$. In order to achieve a higher penetration and utilisation of RES, the RES (WF and PV) nodes should be reserved into the CSN as many as possible considering penetration limits of RESs and operational constraints of the power system. Then the amount of output power and number of CPP could be determined for $G_2(s)$ according to the load reserve constraints and security constraints. On the other hand, the location of the power source nodes, i.e. the number of lines connecting power source nodes with $G_1(s)$, should be taken into account so as to minimise the number of lines added and to reduce the investment cost for reinforcing CSN and critical lines. The second step model of the CSN optimisation for scenario $s \in R$ can be expressed as

$$\max \lambda_2^s = \sum_{p \in V} v_{ps} l_{ps}^{\mathrm{S}} + \theta_2 / \left(1 + \sum_{p \in V} v_{ps} l_{p - G_1(s)}\right) \tag{8}$$

$$\text{s.t.}: \max_t \sum_{p \in \Omega_{\mathrm{WF}}^s} P_{ps}^{\mathrm{W}}(t) / \sum_{k \in \Omega_{\mathrm{LF}}^s} P_{ks}^{\mathrm{L}}(t) \le \gamma_{\mathrm{W}}^s\% \le \gamma_{\mathrm{W0}}\% \tag{9}$$

$$\max_t \sum_{p \in \Omega_{\mathrm{PF}}^s} P_{ps}^{\mathrm{P}}(t) / \sum_{k \in \Omega_{\mathrm{LF}}^s} P_{ks}^{\mathrm{L}}(t) \le \gamma_{\mathrm{P}}^s\% \le \gamma_{\mathrm{P0}}\% \tag{10}$$

$$\sum_{p \in \Omega_{\mathrm{CF}}^s} P_p^{\mathrm{CN}} \ge \max_t \sum_{k \in \Omega_{\mathrm{LF}}^s} P_{ks}^{\mathrm{L}}(t) + P_{\mathrm{R}}(t) - \sum_{p \in \Omega_{\mathrm{WF}}^s} P_{ps}^{\mathrm{W}}(t) - \sum_{p \in \Omega_{\mathrm{PF}}^s} P_{ps}^{\mathrm{P}}(t) \tag{11}$$

$$\sum_{p \in \Omega_{\mathrm{CF}}^s} P_p^{\mathrm{Cm}} \le \min_t \sum_{k \in \Omega_{\mathrm{LF}}^s} P_{ks}^{\mathrm{L}}(t) + P_{\mathrm{R}}(t) - \sum_{p \in \Omega_{\mathrm{WF}}^s} P_{ps}^{\mathrm{W}}(t) - \sum_{p \in \Omega_{\mathrm{PF}}^s} P_{ps}^{\mathrm{P}}(t) \tag{12}$$

$$\sum_{p \in \Omega_{\mathrm{WF}}^s} P_{ps}^{\mathrm{W}}(t) + \sum_{p \in \Omega_{\mathrm{PF}}^s} P_{ps}^{\mathrm{P}}(t) + \sum_{p \in \Omega_{\mathrm{CF}}^s} P_{ps}^{\mathrm{C}}(t) = \sum_{k \in \Omega_{\mathrm{LF}}^s} P_{ks}^{\mathrm{L}}(t) \tag{13}$$

$$P_p^{\mathrm{Cm}} \le P_{ps}^{\mathrm{C}}(t) \le P_p^{\mathrm{CN}} \tag{14}$$

$$0 \le P_{ps}^{\mathrm{W}}(t) \le P_p^{\mathrm{WN}} \tag{15}$$

$$0 \le P_{ps}^{\mathrm{P}}(t) \le P_p^{\mathrm{PN}} \tag{16}$$

$$-S_{ij}^{\max} \le S_{ij}^s(t) \le S_{ij}^{\max} \tag{17}$$

Equations (9) and (10) represent the constraints of penetration limits of wind power and solar power, respectively, by which the output power and number of RESs integrated into $G_2(s)$ are constrained. Equations (11) and (12) constrain the output power and number of CPPs integrated into the CSN $G_2(s)$. Equation (13) represents the power balance constraint in $G_2(s)$. Equations (14)–(16) represent the output power limits for the CPP, WF and PV, respectively. Equation (17) represents the line capacity limits for transmission line (i, j).

In the proposed two-step CSN optimisation models, the first step model aims to determine a connected sub-network $G_1(s)$ of the original power network. The proposed first step model is in the form of a mixed-integer non-linear programming, as seen from (7). Besides, the first step problem aims to determine a connected sub-network G_1(s) with some specified nodes (i.e. critical load nodes), which is essentially a Steiner Tree problem [30]. The Steiner Tree problem is non-deterministic polynomial hard and cannot be solved efficiently at present [30]. Thus, a heuristic algorithm can be utilised to solve the proposed first step model.

On the other hand, the second step model for obtaining the CSN G_2(s) is also a mixed-integer non-linear programming problem. However, this model can be solved using the greedy strategy: (i) firstly, the WF and PV nodes are added into $G_1(s)$ one by one according to their respective rankings until the penetration limits constraints are not met; (ii) secondly, after the WF and PV nodes are reserved into $G_1(s)$, the HEP and TPP nodes can be added into $G_1(s)$ one by one according to the rankings until the load reserve constrains are not met. The greedy strategy for solving the second step model is also illustrated in Fig. 2.

In this work, the quantum artificial bee colony algorithm (QABCA) is applied to solve the first step model [31, 32]. The QABCA integrates the artificial bee colony algorithm (ABCA) with quantum computing theories and by virtues of the advantages of the ABCA and quantum computing, it can reduce the computation complexity and improve the convergence speed of the concerned problem significantly [31, 32]. The main procedures for solving the first step CSN optimisation model using the QABCA are as follows:

(i) Set the iteration limit and set (7) as the fitness function of the QABCA.
(ii) Solve the first step CSN optimisation model and calculate the fitness value.
(iii) If the sub-network optimised by the QABCA is connected, go next.

(iv) If the sub-network optimised by the QABCA is not connected, make it connected using the shortest path between the sub-sub-networks. The shortest path between the sub-sub-networks can be obtained using the Dijsktra's algorithm.
(v) If the iteration limit is reached, terminate the QABCA and output the solutions; otherwise, repeat steps (ii), (iii) and (iv).

4 Statistical salience method for critical lines identification

The statistical salience method is proposed in this section to identify critical lines for each CSN of the corresponding typical scenario. Then the critical lines for the original power system can be attained from those for each CSN.

4.1 ES and NM in complex network

4.1.1 ES of complex network: There are many research works associated with the identification methods of critical lines based on complex network theory, most of which are based on the edge betweenness [10–15]. However, a predefined number of critical lines is indispensable for these betweenness based methods. The concept of ES is proposed in [33] as a robust approach to identify meaningful structural characteristics of complex networks. With the edges classified explicitly into critical ones and non-critical ones, the ES method can overcome the problem of pre-specification of the number of critical lines. Taking into account its advantages, the ES method is proposed to identify critical lines in power networks.

The edge (line) salience method defines the shortest-path tree $\boldsymbol{T}(r)$ that describes the shortest paths from a fixed reference node r to the rest of nodes in the network [33]. $\boldsymbol{T}(r)$ can be represented as a symmetric $n \times n$ matrix with entry $t_{ij}(r) = 1$ if edge (i, j) is part of at least one of the shortest paths from r; otherwise, $t_{ij}(r) = 0$. Based on the average shortest-path tree, the $n \times n$ ES matrix $\boldsymbol{S}$ of the network is defined as

$$\boldsymbol{S} = \langle \boldsymbol{T} \rangle = \sum_r \boldsymbol{T}(r)/n \tag{18}$$

where the entry $s_{ij} \in [0, 1]$ of $\boldsymbol{S}$ quantifies the proportion of shortest-path trees that the edge (i, j) participates in [33]. The larger s_{ij} is, the more important it is. If $s_{ij} = 0$, it means edge (i, j) can be neglected for all reference nodes, and if $s_{ij} = 1$, it means edge (i, j) is indispensable to all reference nodes.

The ES method is not sensitive to the position of the edge, and can be used to identify critical lines without predefining the number of them [33]. However, this method tends to give a higher evaluation to edges adjacent to nodes with low degree [34]. Thus, the NM for power networks is incorporated.

4.1.2 NM of complex network: In statistical mathematics, the null hypothesis is a type of hypothesis test that is designed to describe the statistical relationship between two objects. Commonly, the null hypothesis is intended to be rejected and it proposes no relationship between two concerned objects compared. The comparison is deemed statistically significant if the realisation of the null hypothesis is no more than a significance level.

The various statistics of complex networks, such as degree distribution, clustering coefficient and average shortest path, are not sufficient to fully describe the characteristics of the network [35]. To further investigate and reveal the statistical characteristics of real-world network, the NM of complex networks is first proposed in [36]. NM is originated from the null hypothesis of statistical mathematics and is defined statistically as a randomised network with some of the same statistic characteristics (such as average degree and degree distribution) as the initial network. In [37], the weights to edges are assigned by NM, and a disparity filter method is proposed to extract the connection backbone of the network. In [34], the edge involvement derived from ES and statistical importance derived from NM is proposed, and the critical edges are identified by incorporating these two indexes, which can overcome the shortcomings of ES and attain reasonable results.

NM represents one of the state-of-the-art methods that play significant roles in quantitatively and qualitatively analysing the characteristics of the complex network [34–37]. The combination of ES and NM can attain reasonable results [34]. Based on the ES and NM methods, the statistical salience is proposed in this work to identify critical lines for CSN and the original power system with RESs.

4.2 Statistical salience method for critical lines identification

Based on the ES method [33], the line salience of line (i, j) for CSN $G_2(s)$ of the concerned power network can be defined as

$$e_{ij}^s = \frac{1}{[(N_s^{\mathrm{G}} - 1)(N_s^{\mathrm{L}} - 1)]^{0.5}} \sum_{k \in \Omega_{\mathrm{LF}}^s, k \neq i} \frac{g_{ik}^{(i,j)}}{g_{ik}} \quad \forall i, j \in G_2(s) \tag{19}$$

The shortest paths in (19) are determined using the effective distance (6). The line salience, or ES, indicates the participation level of line (i, j) in the shortest paths from node i to all the load nodes, which can be a proper metric to evaluate the importance of line (i, j). The larger *es ij* is, the more important line (i, j) is.

Based on line salience of line (i, j), a null hypothesis is proposed that line salience of all the connected lines of a specific node (or bus) i with degree k_i is uniformly distributed, i.e. line salience of all the lines of the concerned nodes is assumed to be the same. Then, the statistical salience of line (i, j) for CSN $G_2(s)$ can be presented as

$$J_{ij}^s = 1 - \int_0^{e_{ij}^s} f(x, k_i)\,\mathrm{d}x \tag{20}$$

where $f(x, k_i)$ represents the probability density function of the line salience of node i considering its degree k_i [26]. The smaller J_{ij}^s is, the less satisfied the null hypothesis is and the more important the line (i, j) is. According to the null hypothesis, the probability density function of line salience is an uniform distribution [33]

$$f(x, k_i) = (k_i - 1)(1 - x)^{k_i - 2} \tag{21}$$

With the impacts of node degree considered, the statistical salience of line (i, j) in scenario s can be denoted as (22) [34]

$$J_{ij}^s = \min\{(1 - e_{ij}^s)^{(k_i - 1)}, (1 - e_{ij}^s)^{(k_j - 1)}\} \tag{22}$$

The critical lines can be identified for a given significance level based on the distribution of statistical salience of lines of the power network. After the critical lines of each CSN $G_2(s)$ are obtained, the critical lines of the original power network G_0 can be identified by the calculation of intersection or the entropy weight and TOPSIS method [29]. The procedures of the proposed critical line identification method for power systems with RESs can be illustrated by Fig. 2.

5 Case studies

5.1 Modified IEEE 118-bus system with renewables

The modified IEEE 118-bus system is used to illustrate the effectiveness of the proposed statistical salience method. The system consists of 18 TPPs, 2 HEPs, 14 WFs and 15 PVs. The overall installed MW capacities of TPPs, HEPs, WFs and PVs are 5580, 550, 2000 and 570 MW, respectively. Diagram of the distribution of loads and power sources is shown in Fig. 3. The critical load nodes set by the power system decision maker include nodes 2, 3, 7, 11, 13, 14, 16, 20, 21, 28, 29, 33, 35, 39, 41, 43, 44, 45, 47, 48, 50, 51, 52, 53, 60, 67, 75, 78, 79, 82, 83, 86, 88, 93, 94, 95, 96, 97, 98, 101, 106, 115, 117 and 118. The detailed parameters can be found in [38].

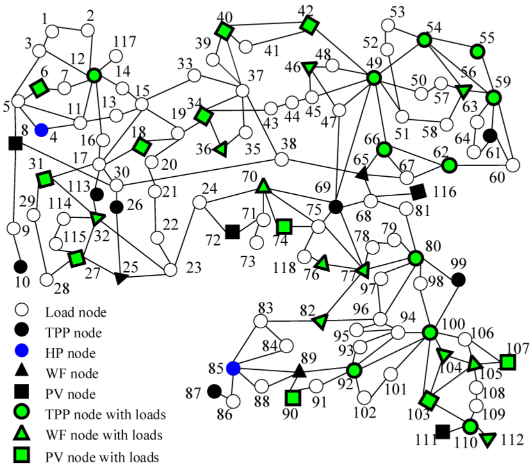


Fig. 3 *Diagram of the modified IEEE 118-bus system with RESs*

Table 2 Optimisation results of CSNs

N_F	Line (i, j)
15	(2, 12), (7, 12), (11, 12), (11, 13), (12, 16), (12, 117), (12, 14), (15, 17), (15, 19), (15, 33), (16, 17), (17, 113), (17, 31), (18, 19), (19, 20), (20, 21), (23, 32), (28, 29), (29, 31), (31, 32), (32, 114), (33, 37), (34, 43), (34, 36), (34, 37), (35, 36), (37, 39), (41, 42), (43, 44), (44, 45), (47, 49), (47, 69), (48, 49), (49, 50), (49, 51), (49, 66), (51, 52), (52, 53), (53, 54), (54, 59), (59, 60), (66, 67), (69, 70), (69, 75), (69, 77), (75, 118), (77, 82), (77, 78), (78, 79), (79, 80), (80, 98), (82, 96), (82, 83), (83, 85), (85, 88), (85, 86), (93, 94), (94, 100), (94, 95), (95, 96), (96, 97), (99, 100), (100, 101), (100, 103), (114, 115)
14	(6, 7), (100, 106), (103, 110)
12	(3, 12), (4, 11), (17, 30)
11	(26, 30), (42, 49)
9	(45, 49)
8	(74, 75)
6	(23, 24), (24, 72), (45, 46), (46, 47)
4	(39, 40), (40, 41), (54, 56), (88, 89), (89, 90)
3	(3, 5), (4, 5), (5, 8), (5, 6), (65, 66), (68, 116), (68, 69)
1	(23, 25), (25, 26), (101, 102), (103, 105), (105, 106)

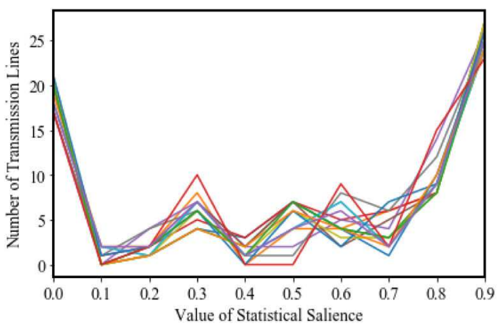


Fig. 4 *Distribution of statistical salience for 15 typical scenarios*

Table 3 Identified critical lines for the modified IEEE 118-bus system

Critical line	Ranking order	Critical line	Ranking order
(12, 16)	1	(17, 31)	9
(69, 77)	2	(49, 51)	10
(15, 17)	3	(16, 17)	11
(47, 49)	4	(34, 43)	12
(47, 69)	5	(82, 96)	13
(34, 37)	6	(33, 37)	14
(94, 100)	7	(15, 33)	15
(77, 82)	8	(11, 12)	16

The original generation data of WFs and PVs are obtained from [39], and 1825 scenarios in the original set are generated. It is assumed that the original set contains all the scenarios that cover any weather conditions. Finally, 15 typical scenarios are attained using the CCSBSR method. The penetration limits of wind power and solar power are 35 and 10%, respectively, for the original power system, and 25 and 7%, respectively, for each CSN. The load reserve capacity is 1.2 times the critical load power. The results of the optimised CSNs for all the typical scenarios are summarised in Table 2, where N_F represents the times that line (i, j) is contained in 15 CSNs, and lines with $N_F = 0$ are not listed in Table 2.

Based on CSN optimisation results, the statistical salience of transmission lines in each typical scenario can be attained. The distribution of line statistical salience for each scenario is shown in Fig. 4. It can be seen from Fig. 4 that there is obviously a bimodal shape regarding the statistical salience which is not relevant to the scenarios. The lines in each CSN gather on both boundaries of the statistical salience, and only a small fraction of lines locates in the middle of the interval. Thus, the lines of the network can be successfully classified into two categories by the statistical salience method, i.e. J_{ij} of the critical lines is close to 0 and that of non-critical lines is close to 1. Since only a small number of lines fall in the middle area of statistical salience, the classification of the transmission lines is statistically acceptable and the lines critical for enhancing resilience and reliability of the power system are attained without pre-specifying the number of critical lines. This characteristic of the statistical salience method is fundamentally different from existing critical lines identification methods such as the betweenness based methods.

As illustrated before, the critical lines for each CSN can be attained effectively by the statistical salience method. After the critical lines of each CSN for the corresponding typical scenario are identified, the critical lines for the power system can be attained by qualitative method, such as intersection method, which gives no information about the ranking order of critical lines, or by quantitative analysis method, such as entropy weight and TOPSIS method [29], which ranks the relative importance of critical lines. In this paper, the intersection method is first applied to identify the critical lines indispensable to all the CSNs, and then the entropy and TOPSIS method are employed to rank their relative importance [29]. The identified critical lines for improving the resilience and reliability of the power system with RESs under severe natural disasters are shown in Table 3.

In order to demonstrate the effectiveness of the final critical lines for each CSN optimised, the critical lines are removed one by one according to their ranking order. After a critical line is removed, some of the critical loads may be unserved and the topological structure of the optimised CSN may be changed (i.e. separated as several sub-networks). In this work, the interrupted critical loads and the connectivity level after the removal of a critical line are used as resilience measures to investigate the impacts of the critical lines on the loading level and topological structure of the concerned power system.

For each typical scenario (note that its resolution is one day, as mentioned in Section 2.2) and every sub-network, the interrupted critical loads are equal to the hourly difference (if greater than zero) between the overall critical loads and the total available generation of power sources summed over 24 h. To facilitate the presentation, the interrupted critical load is normalised by the overall critical load in the concerned day. The interrupted critical loads for each CSN after removing the critical lines one by one are shown in Fig. 5. For each typical scenario, or each CSN, removing the critical lines will result in significant interruption of critical loads. After all 16 critical lines are removed, the share of the lost critical loads accounts for about 40% of the overall critical loads, which validates the effectiveness of the proposed method considering the fact that 16 critical lines are about only one out of five the number of lines of the concerned CSNs.

To further demonstrate the validity of the proposed statistical salience method, comparisons with the random method [10] and the edge betweenness method [14, 15] are conducted. The random method removes randomly the same number of lines as the

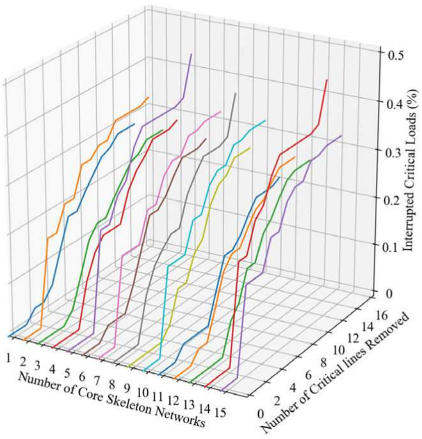
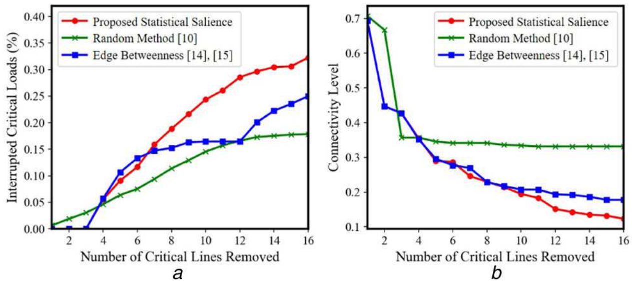
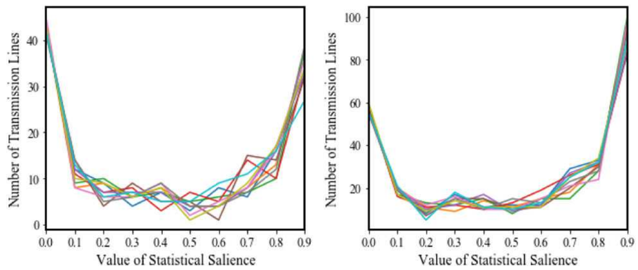


Fig. 5 *Interrupted critical loads in each CSN with critical lines removed*



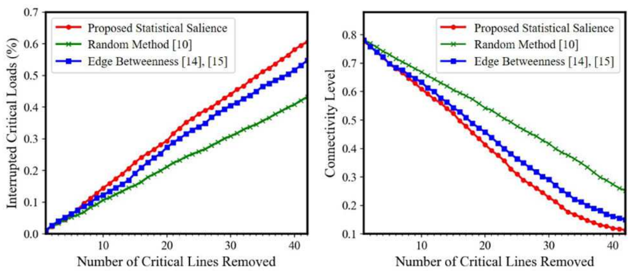
a b

Fig. 6 *Comparison results by removing critical lines for the modified IEEE 118-bus system*
(a) Interrupted critical loads, ***(b)*** Variation of connectivity level



a b

Fig. 7 *Distribution of statistical salience*
(a) GPPS, ***(b)*** ZPPS



a b

Fig. 8 *Comparison results by removing critical lines for GPPS*
(a) Interrupted critical loads, ***(b)*** Variation of connectivity level

statistical salience method. The edge betweenness method is to remove the lines based on the ranking of their edge betweenness. The interrupted critical loads and the connectivity level of the three methods are compared, respectively. The connectivity level is defined as the ratio between the number of nodes in the maximum components and the number of nodes in the original network. The expectation of the interrupted critical loads and the connectivity level on all CSNs are compared in Fig. 6.

As seen from Fig. 6*a*, the interrupted critical loads increase significantly in all the three methods as the number of removed lines increases. The interrupted critical loads in the proposed statistical salience method increase substantially with the increasing number of lines removed. After seven and more critical lines are removed, the interrupted critical loads of the statistical salience method are greater than those of the other two methods. The interrupted critical loads obtained by the random method increase slowly with the increasing number of lines removed, though the obtained interrupted critical loads for removing the first two critical lines are larger than those of the other two methods. Therefore, it can be concluded that the proposed statistical salience method is better than the random method and the edge betweenness method in terms of the interrupted critical loads.

It can be seen from Fig. 6*b* that the connectivity level decreases for all the three methods as the number of lines removed rises. However, the proposed statistical salience method attains the most significant decrease compared with the edge betweenness method and random method after four or more critical lines are removed. In other words, the proposed statistical salience method is better than the random method and the edge betweenness method, and it can effectively identify the critical lines for the power systems with RESs.

5.2 GPPS in China

As mentioned in Section 1, GPPS is one of the regional power systems in China that are vulnerable to natural disasters. The statistical salience method is applied to identify critical lines for GPPS which has 212 transmission lines. The distribution of line statistical salience for GPPS is shown in Fig. 7*a*.

It can be seen from Fig. 7*a* that the values of statistical salience of the transmission lines gather on both boundaries of the distribution and thus the transmission lines can be clearly categorised as critical ones and non-critical ones for each scenario. Forty-two lines are identified as critical ones for GPPS by applying the intersection methods and, to attain the ranking order for comparisons, the entropy and TOPSIS method. By removing the critical lines according to their ranking order, comparisons in interrupted critical loads and connectivity level of the proposed statistical salience method with edge betweenness and random methods are shown in Fig. 8. As seen from Fig. 8, as the number of removed critical lines increases, the proposed statistical salience method attains more interrupted critical loads while less connectivity level than the edge betweenness and random methods.

Based on the simulation results in Figs. 7*a* and 8, the conclusions can be drawn that the critical lines can be identified effectively by using the statistical salience method without a pre-specified number of critical lines, and that the proposed statistical salience method is superior to the edge betweenness and random methods.

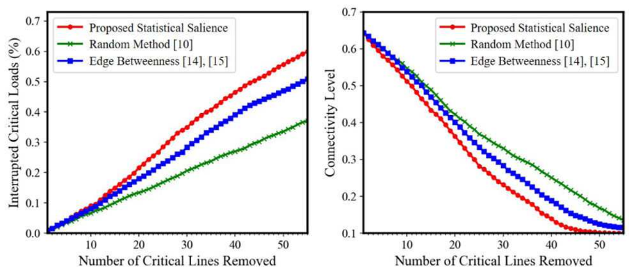
5.3 ZPPS in China

To further validate the effectiveness of the statistical salience method on large power systems, simulations on ZPPS in China, which consists of 525 transmission lines, are also performed. The distribution of line statistical salience for ZPPS is shown in Fig. 7*b*.

As seen from Fig. 7*b*, the statistical saliences of the transmission lines gather on both boundaries of the distribution. As a result, the transmission lines can be classified as critical ones and non-critical ones for each scenario obviously, and the number of critical lines is not required. Fifty-five critical transmission lines are determined finally for ZPPS. By removing the critical lines according to their ranking order, comparisons of the interrupted critical loads and connectivity level by various methods are shown in Fig. 9, which also validate that the proposed statistical salience method is better than the edge betweenness and random methods for identifying critical lines.

6 Conclusion

In this work, the concept of CSN is introduced and a two-step CSN optimisation strategy is presented. Based on the CSN, the critical lines of power systems with RESs are identified by the proposed statistical salience method. Simulations on the modified IEEE 118-



a b

Fig. 9 *Comparison results by removing critical lines for ZPPS*
(a) Interrupted critical loads, ***(b)*** Variation of connectivity level

bus system, GPPS and ZPPS in China verify the effectiveness of the proposed statistical salience methodology for critical lines identification. By using the statistical salience method, transmission lines can be distinctly categorised as critical and non-critical ones while the number of critical lines is not needed. Comparisons show that removal of critical lines identified by the proposed method leads to more interrupted critical loads and a lower connectivity level than removal of those identified by the random method and the edge betweenness method. The comparison results also verify that the statistical salience method is better than the random method and the edge betweenness method and it can effectively identify the critical lines for the power systems with RESs.

In this work, the fragility curve which can innovatively describe the relationship between the components of power systems and the natural disasters as well as the type and characteristics of the natural disasters are not considered. Future works may focus on the critical components identification for power systems with RESs considering the fragility curve as well as the characteristics of the natural disasters.

7 Acknowledgments

This work is jointly supported by National Key R&D Program of China (2016YFB0900100), National Natural Science Foundation of China (51777185) and Zhejiang Provincial Natural Science Foundation of China (LY17E070003).

8 References

[1] Wang, Y., Chen, C., Wang, J., *et al.*: 'Research on resilience of power systems under natural disasters – a review', *IEEE Trans. Power Syst.*, 2016, **31**, (2), pp. 1604–1613
[2] Bhusal, N., Abdelmalak, M., Kamruzzaman, M., *et al.*: 'Power system resilience: current practices, challenges, and future directions', *IEEE Access*, 2020, **8**, pp. 18064–18086
[3] Shao, D., Yin, X., Chen, Q., *et al.*: 'Affects of icing and snow disaster occurred in 2008 on power grids in south China', *Power Syst. Technol.*, 2009, **33**, (5), pp. 38–43
[4] Panteli, M., Mancarella, P.: 'Operational resilience assessment of power systems under extreme weather and loading conditions'. Proc. 2015 IEEE PESGM, Denver, CO, USA, July 2015, pp. 1–5
[5] Panteli, M., Trakas, D.N., Mancarella, P., *et al.*: 'Boosting the power grid resilience to extreme weather events using defensive islanding', *IEEE Trans. Smart Grid*, 2016, **7**, (6), pp. 2913–2922
[6] Panteli, M., Pickering, C., Wilkinson, S., *et al.*: 'Power system resilience to extreme weather: fragility modeling, probabilistic impact assessment, and adaptation measures', *IEEE Trans. Power Syst.*, 2017, **32**, (5), pp. 3747–3757
[7] Lagos, T., Moreno, R., Espinosa, A.N., *et al.*: 'Identifying optimal portfolios of resilient network investments against natural hazards, with applications to earthquakes', *IEEE Trans. Power Syst.*, 2020, **35**, (2), pp. 1411–1420
[8] Liu, Y., Fan, R., Terzija, V.: 'Power system restoration: a literature review from 2006 to 2016', *J. Mod. Power Syst. Clean Energy*, 2016, **4**, (3), pp. 332–341
[9] Gao, W., Zhou, R., Zhao, D.: 'Heuristic failure prediction model of transmission line under natural disasters', *IET Gener. Transm. Distrib.*, 2017, **11**, (4), pp. 935–942
[10] Wang, M., Xiang, Y., Wang, L., *et al.*: 'Critical line identification for hypothesized multiple line attacks against power systems'. Proc. IEEE/PES T&D, Dallas, USA, May 2016, pp. 1–5
[11] Yu, Z., Huang, S., Ma, Z., *et al.*: 'Identification of critical lines in power grid based on electric betweenness entropy'. Proc. IEEE PES APPEEC, Brisbane, Australia, November 2015, pp. 1–5
[12] Bompard, E., Napoli, R., Xue, F.: 'Extended topological approach for the assessment of structural vulnerability in transmission networks', *IET Gener. Transm. Distrib.*, 2010, **4**, (6), pp. 716–724
[13] Alayande, A.S., Jimoh, A.A., Yusuff, A.A.: 'Identification of critical buses and weak transmission lines using inherent structural characteristics theory'. Proc. IEEE PES APPEEC, Brisbane, Australia, November 2015, pp. 1–5
[14] Bompard, E., Luo, L., Pons, E.: 'A perspective overview of topological approaches for vulnerability analysis of power transmission grids', *Int. J. Crit. Infrastruct.*, 2015, **11**, (1), pp. 15–26
[15] Hao, B., Miao, S.: 'Hybrid flow betweenness approach for identification of vulnerable line in power system', *IET Gener. Transm. Distrib.*, 2015, **9**, (12), pp. 1324–1331
[16] Fan, W., Zhang, X., Mei, S., *et al.*: 'Vulnerable transmission line identification using ISH theory in power systems', *IET Gener. Transm. Distrib.*, 2018, **12**, (4), pp. 1014–1020
[17] Fang, J., Su, C., Chen, Z., *et al.*: 'Power system structural vulnerability assessment based on an improved maximum flow approach', *IEEE Trans. Smart Grid*, 2018, **9**, (2), pp. 777–785
[18] Park, S.W., Xu, Q., Hobbs, B.F.: 'Comparing scenario reduction methods for stochastic transmission planning', *IET Gener. Transm. Distrib.*, 2019, **13**, (7), pp. 1005–1013
[19] Heitsch, H., Römisch, W.: 'Scenario reduction algorithms in stochastic programming', *Comput. Optim. Appl.*, 2003, **24**, (2), pp. 187–206
[20] Wang, Y., Liu, Y., Kirschen, D.S.: 'Scenario reduction with submodular optimisation', *IEEE Trans. Power Syst.*, 2017, **32**, (3), pp. 2479–2480
[21] Schlueter, R.A., Park, G.L., Reddoch, T.W., *et al.*: 'A modified unit commitment and generation control for utilities with large wind generation penetrations', *IEEE Trans. Power App. Syst.*, 1985, **104**, (7), pp. 1630–1636
[22] Liao, P., Li, X.: 'A survey on calculation methods of wind power penetration limit', *Power Syst. Technol.*, 2008, **32**, (10), pp. 50–53
[23] Papathanassiou, S.A., Boulaxis, N.G.: 'Power limitations and energy yield calculation for wind farms operating in island systems', *Renew. Energy*, 2006, **31**, (4), pp. 457–479
[24] Chang, C.-A., Wu, Y.-K., Chen, B.-K.: 'Determination of maximum wind power penetration in an isolated island system by considering spinning reserve', *Energies*, 2016, **9**, (9), p. 688
[25] Ren, Z., Shao, F., Liu, J., *et al.*: 'Node importance measurement based on the degree and clustering coefficient information', *Acta Phys. Sin.*, 2013, **62**, (12), p. 128901
[26] Du, Y., Gao, C., Chen, X., *et al.*: 'A new closeness centrality measure via effective distance in complex networks', *Chaos*, 2015, **25**, (3), pp. 440–442
[27] Brockmann, D., Helbing, D.: 'The hidden geometry of complex, network-driven contagion phenomena', *Science*, 2013, **342**, (6164), pp. 1337–1342
[28] Dierauf, T., Growitz, A., Kurtz, S., *et al.*: 'Weather-corrected performance ratio'. NREL, Golden, CO, USA, April 2013, Tech. Rep. NREL/TP-5200-57991
[29] Li, X., Wang, K., Liu, L., *et al.*: 'Application of the entropy weight and TOPSIS method in safety evaluation of coal mines', *Procedia Eng.*, 2011, **26**, (4), pp. 2085–2091
[30] Sadeghi, A., Fröhlich, H.: 'Steiner tree methods for optimal sub-network identification: an empirical study', *Bmc Bioinformatics*, 2013, **14**, (144), pp. 1–19
[31] Abbas, N.H., Aftan, H.S.: 'Quantum artificial bee colony algorithm for numerical function optimization', *Int. J. Comput. Appl.*, 2014, **93**, (9), pp. 28–33
[32] Karaboga, D., Basturk, B.: 'A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm', *J. Glob. Optim.*, 2007, **39**, (3), pp. 459–471
[33] Grady, D., Thiemann, C., Brockmann, D.: 'Robust classification of salient links in complex networks', *Nat. Commun.*, 2012, **3**, (3), pp. 199–202
[34] Zhang, X.H., Zhang, Z.C., Zhao, H., *et al.*: 'Extracting the globally and locally adaptive backbone of complex networks', *PLOS One*, 2014, **9**, (6), p. e100428
[35] Milo, R., Itzkovitz, S., Kashtan, N., *et al.*: 'Superfamilies of evolved and designed networks', *Science*, 2004, **303**, (5663), pp. 1538–1542
[36] Maslov, S., Sneppen, K.: 'Specificity and stability in topology of protein networks', *Science*, 2002, **296**, (5569), pp. 910–913
[37] Serrano, M.Á., Boguná, M., Vespignani, A.: 'Extracting the multiscale backbone of complex weighted networks', *Proc. Natl. Acad. Sci.*, 2009, **106**, (16), pp. 6483–6488
[38] 'Illinois Institute of Technology'. Available at http://motor.ece.iit.edu/data/, accessed 30 April 2018
[39] 'Renewable Sources Generation Estimate'. Available at http://www.ceps.cz/ENG/Data/Vsechna-data/Pages/odhad-vyroby-obnovitelnych-zdroju.aspx/, accessed 30 April 2018