Electrical Power and Energy Systems xxx (2011) xxx–xxx

Contents lists available at SciVerse ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

A new approach for power system black-start decision-making with vague set theory

Shunqi Zeng [a], Zhenzhi Lin [b], Fushuan Wen [b,c,*], Gerard Ledwich [c]

[a] School of Electrical Engineering, South China University of Technology, Guangzhou 510640, China
[b] School of Electrical Engineering, Zhejiang University, Hangzhou 310027, China
[c] School of Engineering Systems, Queensland University of Technology, Gardens Point, Brisbane, Queensland 4001, Australia

ARTICLE INFO

Article history:
Received 19 February 2011
Received in revised form 8 September 2011
Accepted 16 September 2011
Available online xxxx

Keywords:
Power system restoration
Black-start
Decision-making
Vague set
Interactions among indexes

ABSTRACT

Power system restoration after a large area outage involves many factors, and the procedure is usually very complicated. A decision-making support system could then be developed so as to find the optimal black-start strategy. In order to evaluate candidate black-start strategies, some indices, usually both qualitative and quantitative, are employed. However, it may not be possible to directly synthesize these indices, and different extents of interactions may exist among these indices. In the existing black-start decision-making methods, qualitative and quantitative indices cannot be well synthesized, and the interactions among different indices are not taken into account. The vague set, an extended version of the well-developed fuzzy set, could be employed to deal with decision-making problems with interacting attributes. Given this background, the vague set is first employed in this work to represent the indices for facilitating the comparisons among them. Then, a concept of the vague-valued fuzzy measure is presented, and on that basis a mathematical model for black-start decision-making developed. Compared with the existing methods, the proposed method could deal with the interactions among indices and more reasonably represent the fuzzy information. Finally, an actual power system is served for demonstrating the basic features of the developed model and method.

1. Introduction

After a global blackout or local outage, the power system concerned should be restored as soon as possible. The power system restoration process after a global blackout could be divided into three phases: the black-start phase, the network reconfiguration phase and the load restoration phase. Among these three phases, the black-start phase is defined as the one in which the black-start units, after a large-area blackout, supply power to the non-black-start units without the help of other systems and then gradually expand the re-supplied areas until the entire power system is restored. Thus, the black-start process is the first stage for quickly restoring power supply, and optimizing the black-start schemes is one of the most significant issues having impacts on the system restoration speed. A computer-aided support system for black-start decision-making, as an important component of a smart grid, could implement the online evaluation and optimization of the black-start schemes [1–3]. Up to now, the available literature on black-start decision-making is mainly focused on the selection of the optimal black-start scheme [4,5].

In order to comprehensively evaluate the candidate black-start schemes, both qualitative and quantitative indices are usually employed. In [6], accurate numbers were employed to scale qualitative indices for comparing and synthesizing qualitative indices with quantitative ones. However, a fuzzy number is more reasonable to signify the value of quantitative indices than accurate numbers as clarified in [7] and employed for black-start decision-making [8]. Nevertheless, the fuzzy number is unable to represent all kinds of complicated relationships among indexes [9].

For evaluating and optimizing black-start schemes, many methods have been developed in recent years. In [10], a hierarchical black-start case-based library is defined and a hierarchical black-start case-based reasoning algorithm for black-start decision-making presented, but technical constraints are not fully taken into account. In [11], a DEA based evaluation method for black-start decision-making is presented, in which the estimated indices of the black-start schemes are divided into two categories, i.e., the input ones and output ones. However, the decision-making results such obtained might be far from the expected one since this method over-depends on objective data and experts' experience is not employed in designing black-start schemes. In summary, most existing decision-making methods for selecting the optimal black-start scheme depend on an individual decision-making method, while in practice the back-start scheme is usually deter-

* Corresponding author at: School of Electrical Engineering, Zhejiang University, Hangzhou 310027, China.
E-mail address: fushuan.wen@gmail.com (F. Wen).

0142-0615/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.ijepes.2011.09.012

mined by a group of experts or dispatchers. With this in mind, a group decision-making method for optimizing the black-start scheme is presented in [12], and the procedure of this method is closer to actual situations.

In the existing methods for black-start decision-making, the selected indexes are supposed to be mutually independent. However, some interactions may indeed exist among the indices. To the best of our knowledge, up to now no research work has been reported on how to reasonably take into account of the interactions among indexes when making black-start decisions.

The vague set theory is proposed in 1993 and has gradually become more and more popular for handling decision-making problems [11], due to its more powerful expression ability than fuzzy numbers, as well as the ability of vague-valued fuzzy measures for modeling the interactions among indices. Hence, the vague set theory provides a tool for properly formulating the black-start decision-making problem as well as for modeling the interactions among indexes. Given this background, the vague set concept and vague-valued fuzzy measures are first introduced in Section 2. Then, taking the interactions among indices into account, a group decision-making model based on the vague set theory is developed. In Section 3, a decision-making method for determining the optimal black-start scheme is presented based on the non-linear additive measure. Finally, a numerical example from an actual power system is served for demonstrating the essential features of the proposed method in Section 4. Concluding remarks are given in Section 5.

2. The vague set theory

2.1. Definition of vague sets

Let U be the universe of discourse, with the element of U denoted by x. A vague set A in U is characterized by a pair of membership functions $t_A(x)$ and $f_A(x)$,

$$t_A(x): \ U \to [0,1], \quad f_A(x): \ U \to [0,1]$$

where $t_A(x)$ is the truth-membership function of vague set A, which is a lower bound on the grade of membership of x derived from the evidence for x, and $f_A(x)$ is the false-membership function of vague set A, which is a lower bound on the negation of x derived from the evidence against x, such that $0 \leqslant t_A(x) + f_A(x) \leqslant 1$. For instance, Fig. 1 shows a vague set in the universe of discourse U. Note that the vague set is the same with the intuitionistic fuzzy set in essence according to some research work. Vague set A will be written as $(x, t_A(x), f_A(x))$ or $(t_A(x), f_A(x))$ in this paper [9,13].

2.2. Vague-value fuzzy measures

The set, $L = \{(x_1, x_2); x_1, x_2 \in [0,1], x_1 + x_2 \leqslant 1\}$, is important in the vague set theory and can be organized as a complete lattice by: $\forall A, B \in L$, $A = (t_1, f_1)$, $B = (t_2, f_2)$, $A \leqslant_L B$ if $t_1 \leqslant t_2, f_2 \leqslant f_1$, and

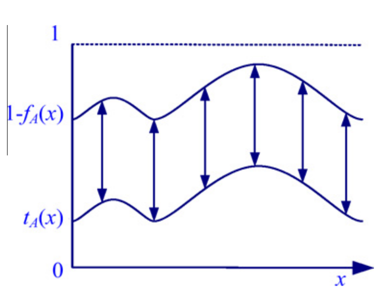

Fig. 1. A vague set.

$$A \wedge B = (\min(t_1, t_2), \max(f_1, f_2))$$
$$A \vee B = (\max(t_1, t_2), \min(f_1, f_2)). \tag{1}$$

The lattice is denoted as $(L, \leqslant L)$. Thus, the vague set $A = (x, t_A(x), f_A(x))$ in the universe of discourse U is equivalent to an element of set L in the complete lattice $(L, \leqslant L)$, namely the mapping $A{:}U \to L{:}x \mapsto (t_A(x), f_A(x))$.

Definition. Let $(U, \Re)$ be a measurable space, where $\Re$ is the universe σ in U. A vague-valued fuzzy measure over a measurable space $(U, \Re)$ is a mapping $\tau : \Re \to L$ with the following properties [14,15]:

(i) $\tau(\varnothing) = (0, 1)$, $\tau(U) = (1, 0)$;
(ii) $\forall A, B \in \Re$, $A \subset B$ implies $\tau(A) \leqslant_L \tau(B)$.

2.3. The Sugeno operator

Theorem. Let $(U, \Re)$ be a measurable space, $\tau : \Re \to L$ be a vague-valued fuzzy measure, and $\tilde{f} : U \to L$ be a vague-value mapping where $\Re$ is measurable. For each $A \in \Re$, the vague-valued Sugeno integral of $\tilde{f}(x)$ concerning τ in set A can be defined as follows [9]:

$$(S_l) \int_A \tilde{f}(x) d\tau = \sup_{\alpha \in L}{}_L \inf{}_L [\alpha, \tau(\widetilde{F}_\alpha \cap A)] \tag{2}$$

where $\widetilde{F}_\alpha = \{x \in X; \tilde{f}(x) \geqslant_L \alpha\}$, $\alpha \in L$. When $A = U$, the integral can be abbreviated as:

$$(S_l) \int \tilde{f}(x) d\tau = \sup_{\alpha \in L}{}_L \inf{}_L [\alpha, \tau(\widetilde{F}_\alpha)] \tag{3}$$

2.4. Rules of ranking

Suppose that there are m schemes to be estimated, and the comprehensive evaluation value of scheme i is the vague value $V_i = (t_i, f_i)$ $(i = 1, 2, \ldots, m)$. For the sake of ranking all the schemes in the order of their superiority, score functions are introduced as follows [9]:

$$P_1 = t_i - f_i \tag{4}$$

$$P_2 = 1 - f_i \tag{5}$$

The sorting rule is defined as: at first the ranking is based on the value of P_1, and the larger P_1 is, the better the scheme will be; if P_1 takes the same value for two/more schemes, then the scheme with the larger/largest P_2 will be the better/best one.

3. A Black-start decision-making method based on vague set theory

3.1. Black-start decision-making process

Generally speaking, the framework of the support system for black-start decision-making includes three functional modules, i.e., development, verifications and selection/optimization of black-start strategies. The support system will search the topological database according to the locations of black-start units. Then, all possible black-start schemes will be generated automatically by ascertaining the power plants to be restarted and possible supplying paths to restart them. Afterwards, a series of technical verifications will be done to check the black-start schemes, including self-excitation analysis of the black-start units, over-voltage verifications, system frequency verifications, examinations of low frequency oscillation and transient stability. Finally, an optimal black-start scheme will be selected from the candidate schemes after verifications. The optimization of black-start schemes is of great importance and plays a paramount role in the black-start decision support system [16,17]. A decision-making method for optimizing black-start schemes based on vague-valued fuzzy measures will be presented below.

3.2. Indices in the black-start decision-making process

The black-start scheme can be affected by many factors. Power system dispatchers or experts associated could choose indices which comprehensively reflect and measure the advantages and disadvantages of the candidate black-start schemes, and generally both qualitative and quantitative indices are involved. For example, four indices were chosen in the developed methods in [6], including the rating capacity of each unit, the number of switch operations, the start-up time of each unit, and a qualitative index, i.e., the importance of the load along the charging path. Quantitative indices of different units could be compared with each other after being normalized, while qualitative indices need to be scaled before being synthesized with quantitative ones.

The vague set is of a stronger ability than the traditional fuzzy set in dealing with uncertain information, since the former takes both the positive and negative aspects into account. Therefore, values in the form of the vague set are used to represent the evaluation indices associated with black-start schemes. The transformation rules between qualitative indices and vague values are listed in Table 1 [9].

As shown in Table 1, (good, bad) is a set of linguistic variables expressing the qualitative indices, which can be changed to (high, low) or (hot, cold) according to the actual situations.

The normalizing method of the indices is needed in making black-start decision, and is described as follows. Given an evaluating problem with m evaluating indices and n evaluated objects (schemes), a $m \times n$ evaluating matrix $\mathbf{R}' = (r'_{ij})_{m\times n}$ is obtained through the combination of the quantitative and qualitative parameters, after the quantitative indices are represented by vague values, where $r'_{ij} = (t'_{ij}, f'_{ij})$. Then, the evaluating matrix $\mathbf{R}'$ is translated to $\mathbf{R} = (r_{ij})_{m\times n}$ through normalization where $r_{ij} = (t_{ij}, f_{ij})$ and $t_{ij}, f_{ij} \in [0,1]$. r_{ij} represents the value of the ith index related to the jth evaluated object, and is calculated by:

$$r_{ij} = \left(\frac{t'_{ij}}{1-\min\limits_j\{f'_{ij}\}}, \max\left(1-\frac{1-f'_{ji}}{\max\limits_j\{t'_{ij}\}}, 0\right)\right)(i \in I_1) \quad (6)$$

$$r_{ij} = \left(\min\left(1, \frac{1-\max\limits_j\{f'_{ij}\}}{t'_{ij}}\right), 1-\frac{\min\limits_j\{t'_{ij}\}}{1-f'_{ij}}\right)(i \in I_2) \quad (7)$$

where I_1 is the index related to profitability, and I_2 the one related to loss.

Table 1
Seven-grade linguistic variables expressed in vague values.

Grade	Vague-value
Ultra good	(0.9,0)
Very good	(0.75,0.1)
Good	(0.6,0.25)
Medium	(0.45,0.4)
Bad	(0.3,0.55)
Very bad	(0.15,0.7)
Ultra bad	(0,0.85)

3.3. Weights and interactions among indexes

As mentioned before, the evaluating indices employed for evaluating the black-start schemes are usually not completely independent. For example, according to [7], the increase in the number of substations would prolong the starting time, which means these two factors are correlated. According to [12], the larger the ratio capacity of the unit to be started is, the more the start-up power will be needed. On the other hand, the state of a generator unit could have some impact on the actual start-up time. In other words, these indices are correlated.

The examples from some existing publications as stated above illustrate the existence of interactions among various indices. However, the existing methods for optimizing the black-start schemes in available publications are not able to deal with the interactions among various indices. For example, the four indices in [7] are denoted by $C = \{c_1, c_2, c_3, c_4\}$, of which the two indices c_1 and c_2 are correlated, and the values of c_1 and c_2 are linearly weighted and finally aggregated. However, since there is an overlap between c_1 and c_2 in reflecting the goodness degrees of the black-start schemes, the weighted values of the index subset $\{c_1, c_2\}$ should be less than the linear sum of the weighted value of $\{c_1\}$ and $\{c_2\}$. As shown in Fig. 2, the size of the geometry represents the weighted values of the indexes, and τ is the weight.

Fig. 2a shows that the two indices are independent with each other, and the weights can be summed up linearly, i.e. $\tau_{1\cup 2} = \tau_1 + \tau_2$. Fig. 2b illustrates that the relationship between the two indices is including and included, and in this case $\tau_{1\cup 2} = \max(\tau_1, \tau_2)$. In Fig. 2c, there is an interaction between the two indices, and in this case $\tau_{1\cup 2} < \tau_1 + \tau_2$ or $\tau_{1\cup 2} = \tau_1 + \tau_2 - \tau_{1\cap 2}$, and this means that the indices could not be evaluated independently. The relationship among indices is very complicated and difficult to determine, while the vague sets provide a tool for solving this problem.

The weights for indexes have to be properly determined during the black-start decision-making process, since the weights have impacts on the evaluation of the candidate schemes. Furthermore, the experience from domain experts should be fully employed in recognizing the interactions among various indices as well as determining the weights.

3.4. Methods of determining the weights

The procedure to determine the weights of indices associated with black-start schemes are as follows:

(1) Subjective weights can be specified by domain experts.

Subjective weights can be directly assigned by domain experts, or be determined via pair-wise comparisons. The pair-wise comparisons are used to determine which one in a pair of indices is more important than the other one, and finally produce a judging matrix of relative importance [18,19].

(2) Objective weights can be calculated with objective data. For example, the method based on the entropy weight theory could be used to determine the objective weights [6].

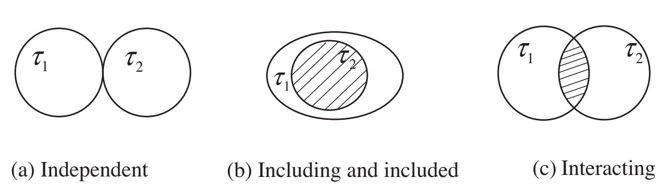

Fig. 2. The relationships between two indices.

Please cite this article in press as: Zeng S et al. A new approach for power system black-start decision-making with vague set theory. Int J Electr Power Energ Syst (2011), doi:10.1016/j.ijepes.2011.09.012

The vague value will be employed in the procedure of modeling and determining the subjective weights, and is a focus of this work. On the other hand, a method for determining the objective weights can be found in [6].

3.5. A black-start decision-making scheme based on vague fuzzy measures

The black-start decision-making is best modelled as a group decision-making and yet multicriteria problem. As discussed before, if the interactions among various indices are taken into account, then the traditional linear operator is no longer applicable. Hence, a method based on the theory of non-linear-additive measures, and more specifically the Sugeno integral operator, is employed. The Sugeno integral operator differs from the traditional integral operator by its fundamental rule of "maximin operator–minimax operator (∨-∧)". As the number of the evaluation indices and the number of participating domain experts are limited in the black-start decision-making problem, the Sugeno integral operator is then used with the discrete form as detailed below.

Let $U = \{c_1, c_2, \ldots, c_n\}$, and the function value of c_i is $x_i = (t_i, f_i) \in L$. In other words, x_i can be expressed in a discrete form like $x_1, x_2, \ldots, x_n$. $\tau = (\tau_t, \tau_f)$ is defined as a vague-valued fuzzy measure of the power set of U, and the vague value Sugeno integral S: $L^n \to L$ is defined by

$$S(x_1, x_2, \ldots, x_n) = \left(\bigvee_{i=1}^{n} \left[t_{(i)} \wedge \tau_t(\{c_{(i)}, \ldots, c_{(n)}\}) \right], \bigwedge_{i=1}^{n} \left[f_{(i)} \vee \tau_f(\{c_{(1)}, \ldots, c_{(i)}\}) \right] \right) \quad (8)$$

where $c_{(i)} \in U$; $x_{(i)}$ is obtained after reordering the primitive function x_i such that $t_{(1)} \leqslant t_{(2)} \leqslant \cdots \leqslant t_{(n)}, f_{(1)} \geqslant f_{(2)} \geqslant \cdots \geqslant f_{(n)}$.

The black-start decision-making method based on vague-valued fuzzy measures could be described as follows: the initial value of each index in the candidate black-start schemes should first be specified, and then be transferred into vague values. The weights associated with indexes and the values associated with interactions are given by domain experts, and the Sugeno integral operator based on the non-additive measure is next used for non-linear aggregation. Suppose that the set of evaluation indices is denoted by $C = \{c_1, c_2, \ldots, c_n\}$, and the values of indices $X = \{x_1, x_2, \ldots, x_n\}$ with $x_i = (t_i, f_i) \in L$. The vague-valued weight of each subset in C is $\tau_{P(C)} = (\tau_t, \tau_f)$, so the value of the comprehensive evaluation of the candidate scheme can be calculated as

$$V = S(x_1, x_2, \ldots, x_n) \quad (9)$$

The domain experts' accumulated appraisal can be determined after each expert's appraisal value is obtained by using Eq. (9). Suppose that there are K domain experts participating in the selection/optimization of black-start schemes as denoted by a set $E = \{e_1, e_2, \ldots, e_K\}$, and the weights associated with each subset of E is $\tau_{P(E)} = (\tau_t, \tau_f)$, then if the calculated comprehensive evaluation of the scheme by expert e_k is denoted as V^k, then the group decision-making appraisal value is given as

$$\overline{V} = S(V^1, V^2, \ldots, V^K) \quad (10)$$

The group decision-making appraisal values of all the schemes can be obtained by Eqs. (9) and (10). At last, the schemes are ranked using the rules mentioned in Section 2 according to their merit order.

In summary, as shown in Fig. 3, the basic procedure of the developed black-start decision-making method can be described as follows:

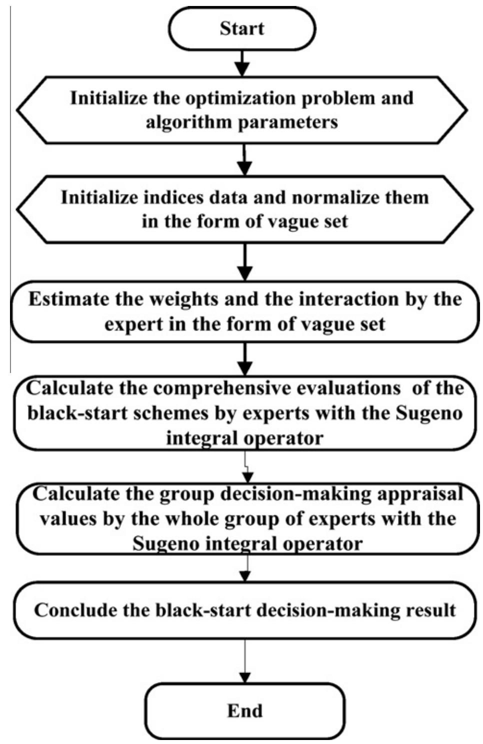

Fig. 3. The procedure of the developed black-start decision-making method.

(1) Each index value associated with the candidate black-start schemes is transformed into a vague value, and then normalized.
(2) The weights associated with evaluation indexes and the interactions among the subsets in the index set C should be ascertained by domain experts, and be expressed as vague values.
(3) The comprehensive evaluation V_i^k of the black-start scheme i by expert e_k is determined with the Sugeno integral operator.
(4) The group decision-making appraisal value $\overline{V}_i$ of the scheme i by the whole group of experts is determined with the Sugeno integral operator.
(5) All the group decision-making appraisal values for all candidate schemes can be obtained by repeating Steps (3) and (4).
(6) All the group decision-making appraisal values of the schemes are ranked according to their merit order by using Eqs. (4) and (5).

4. Case studies

To demonstrate the basic features of the developed model and method based on the vague set theory, a simplified power system structure as shown in Fig. 4 representing a part of the Guangdong power system in China, will be employed here for case studies. Suppose that the black-start unit is located in Plant XNP and has restarted after a blackout, 21 candidate black-start schemes as listed in Table 2 are selected by domain experts. The black-start unit located in Plant XNP would provide the start-up power supply to 21 non-black-start units. The major indices used for selecting the optimal black-start scheme are the rating capacity of each unit denoted as c_1, the unit state as c_2, the start-up power of each unit as c_3, the ramping ratio of each unit as c_4, and the number of switch operations along the restoration paths as c_5. Suppose that there are three domain experts.

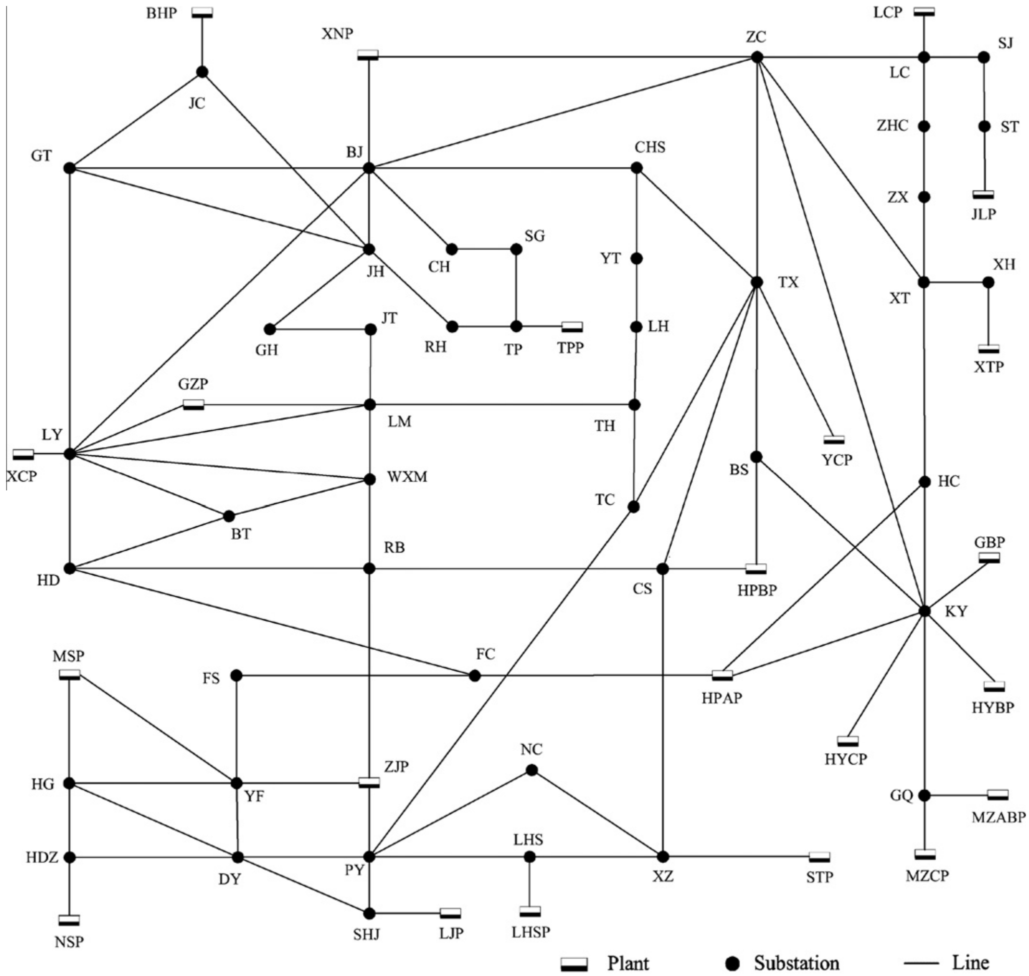

Fig. 4. A simplified power system structure for case studies.

Table 2
The candidate black-start schemes.

Scheme no.	The black-start paths of the candidate schemes
S_1	XNP → BJ → GT → JC → BHP
S_2	XNP → BJ → LY → XCP
S_3	XNP → BJ → LY → GZP
S_4	XNP → BJ → CH → SG → TP → TPP
S_5	XNP → ZC → LC → LCP
S_6	XNP → ZC → LC → SJ → ST → JLP
S_7	XNP → ZC → XT → XH → XTP
S_8	XNP → ZC → KY → GBP
S_9	XNP → ZC → KY → GQ → MZABP
S_{10}	XNP → ZC → KY → GQ → MZCP
S_{11}	XNP → ZC → KY → HYBP
S_{12}	XNP → ZC → KY → HYCP
S_{13}	XNP → ZC → KY → HPAP
S_{14}	XNP → ZC → TX → BS → HPBP
S_{15}	XNP → ZC → TX → YCP
S_{16}	XNP → ZC → TX → CS → XZ → STP
S_{17}	XNP → ZC → TX → TC → PY → LHS → LHSP
S_{18}	XNP → ZC → TX → TC → PY → ZJP
S_{19}	XNP → ZC → TX → TC → PY → SHJ → LJP
S_{20}	XNP → ZC → TX → TC → PY → DY → HDZ → NSP
S_{21}	XNP → ZC → TX → TC → PY → DY → YF → MSP

4.1. The index values and the normalization

For the convenience of presentation, the 21 candidate schemes are denoted as a set $S = \{s_1, s_2, \ldots, s_{21}\}$, and the indices as $C = \{c_1, c_2, \ldots, c_5\}$, the experts as $E = \{e_1, e_2, e_3\}$, the values of the indices as **R**, the weight value of c_i as $\tau(\{c_i\})$, and the amount of interactions between c_i and c_j as $\tau_{c_i \cap c_j}$ such that $\tau(\{c_i, c_j\}) = \tau(\{c_i\}) + \tau(\{c_j\}) - \tau_{c_i \cap c_j}$. $p(\cdot)$ represents the subsets, and for example, $p(C)$ is the subsets of **C**. Detailed data are listed in Table 3, and there are 21 schemes to be evaluated with five indices involved. The evaluating matrix, denoted as $\mathbf{R}'$, can be obtained and translated into a normalized matrix **R** by applying the normalization procedure as formulated in Eqs. (6) and (7).

4.2. The values of weights from domain experts

A power system with weak interconnections is more likely to suffer local blackouts than a tightly interconnected power system. Experience from local blackouts could be gained and used for guiding the future system restoration. Suppose that the weights associated with indices and the degrees of interactions among various indices are given by domain experts, as listed in Tables 4 and 5.

In this case, as shown in Table 4, it is supposed that the three domain experts agree with each other on the existence of interactions among indices c_1, c_3 and c_4. In fact, as calculated with the data listed in Table 3, the correlation coefficients between these three indices are rather large. The correlation coefficient between c_1 and c_3 is 0.925, and that between c_1 and c_4 is 0.904. Thus, the degree of the interaction between each two from these three indices should not be ignored and has to be determined by domain experts with experience. As already mentioned before, the relationship

Table 3
The values of indexes used to evaluate the candidate black-start schemes.

Scheme no.	Plant	Rating capacity (MW)	Unit state	Start-up power (MW)	Ramping ratio (MW/h)	Number of switch operation
S_1	BHP	25.0	Cold (3)	0.400	11.25	4
S_2	XCP	192.0	Warm (5)	0.430	76.80	3
S_3	GZP	255.0	Warm (5)	3.500	102.00	3
S_4	TPP	51.0	Ultra-cold (1)	0.100	25.00	5
S_5	LCP	25.0	Ultra-cold (1)	0.050	10.00	3
S_6	JLP	88.0	Warm (5)	0.200	20.00	5
S_7	XTP	60.0	Cold (3)	0.150	15.00	4
S_8	GBP	47.5	Cold (3)	0.150	23.75	3
S_9	MZABP	38.0	Hot (7)	0.052	11.45	4
S_{10}	MZCP	138.5	Ultra-hot (9)	0.700	41.50	4
S_{11}	HYBP	150.0	Hot (7)	3.000	30.00	3
S_{12}	HYCP	420.0	Ultra-hot (9)	8.000	84.00	3
S_{13}	HPAP	500.0	Warm (5)	7.000	100.00	3
S_{14}	HPBP	600.0	Warm (5)	9.000	120.00	4
S_{15}	YCP	100.0	Ultra-hot (9)	4.000	40.00	3
S_{16}	STP	55.0	Ultra-hot (9)	0.800	13.75	5
S_{17}	LHSP	107.5	Ultra-hot (9)	0.100	32.25	6
S_{18}	ZJP	600.0	Hot (7)	15.000	90.00	5
S_{19}	LJP	84.0	Ultra-cold (1)	0.200	20.00	6
S_{20}	NSP	115.5	Warm (5)	0.250	40.50	7
S_{21}	MSP	103.0	Cold (3)	0.900	15.45	7

Table 4
The weights of the indices.

Weights of index	Expert 1	Expert 2	Expert 3
$\tau(\{c_1\})$	(0.20,0.70)	(0.15,0.75)	(0.25,0.65)
$\tau(\{c_2\})$	(0.25,0.65)	(0.05,0.85)	(0.2,0.7)
$\tau(\{c_3\})$	(0.15,0.75)	(0.20,0.70)	(0.15,0.75)
$\tau(\{c_4\})$	(0.15,0.75)	(0.30,0.60)	(0.25,0.65)
$\tau(\{c_5\})$	(0.15,0.75)	(0.25,0.65)	(0.15,0.75)

Table 5
The degrees of interactions among indices.

Degrees of interactions	Expert 1	Expert 2	Expert 3
$\tau_{c1\cap c3}$	(0.10,0.90)	(0.05,0.95)	(0.10,0.90)
$\tau_{c1\cap c4}$	(0.05,0.95)	(0.05,0.95)	(0.10,0.90)
$\tau_{c3\cap c4}$	(0.05,0.95)	(0.10,0.90)	(0.05,0.95)

among indices is very complicated and difficult to determine, so the vague sets are employed here for the representation of the weights.

In order to obtain the group decision-making result, the weights of the three experts as denoted by $\tau = (\tau_t, \tau_f)$ have to be assigned, and are supposed to be as follows:

$$\tau(\{e_1\}) = (0.3, 0.6), \quad \tau(\{e_2\}) = (0.4, 0.5),$$
$$\tau(\{e_3\}) = (0.4, 0.3), \quad \tau(\{e_1, e_2\}) = (0.6, 0.2),$$
$$\tau(\{e_1, e_3\}) = (0.7, 0.1), \quad \tau(\{e_2, e_3\}) = (0.7, 0.2),$$
$$\tau(\{e_1, e_2, e_3\}) = (1, 0)$$

Afterwards, this decision-making problem can be solved by the proposed method, and the results are detailed below.

4.3. Numerical results

The group decision-making appraisal value of each candidate scheme can be obtained by using Eqs. (9) and (10). As shown in Table 6, the group decision-making appraisal values of the 21 candidate schemes with the interactions among indices considered are listed and abbreviated as VWI. According to the order illustrated in Table 6, the preferred sequence of the schemes is:

Table 6
The optimization order according to subjective weights.

Scheme no.	VWI	Order of VWI	VWOI	Order of VWOI
S_1	(0.30,0.60)	19	(0.273,0.459)	16
S_2	(0.60,0.40)	7	(0.459,0.358)	6
S_3	(0.40,0.35)	1	(0.358,0.273)	5
S_4	(0.33,0.33)	11	(0.333,0.333)	9
S_5	(0.50,0.40)	12	(0.392,0.346)	10
S_6	(0.35,0.70)	13	(0.273,0.626)	17
S_7	(0.55,0.55)	16	(0.49,0.49)	13
S_8	(0.35,0.40)	17	(0.333,0.273)	14
S_9	(0.50,0.60)	6	(0.392,0.6)	7
S_{10}	(0.25,0.40)	9	(0.25,0.338)	11
S_{11}	(0.30,0.50)	14	(0.273,0.54)	18
S_{12}	(0.36,0.15)	2	(0.36,0.25)	2
S_{13}	(0.50,0.50)	3	(0.552,0.552)	3
S_{14}	(0.45,0.50)	5	(0.54,0.552)	4
S_{15}	(0.50,0.25)	15	(0.552,0.33)	12
S_{16}	(0.45,0.45)	10	(0.54,0.54)	19
S_{17}	(0.30,0.20)	8	(0.3,0.25)	8
S_{18}	(0.25,0.45)	4	(0.25,0.54)	1
S_{19}	(0.45,0.50)	21	(0.54,0.5)	21
S_{20}	(0.25,0.65)	18	(0.25,0.688)	15
S_{21}	(0.57,0.57)	20	(0.571,0.571)	20

$$S_3 > S_{12} > S_{13} > S_{18} > S_{14} > S_9 > S_2 > S_{17} > S_{10} > S_{16} > S_4 > S_5 > S_6 > S_{11} > S_{15} > S_7 > S_8 > S_{20} > S_1 > S_{21} > S_{19}$$

Hence, these schemes will be considered according to this order. When the interactions among indexes are taken into account, the 3rd scheme is the best, and the 12th one the second. Thus, the black-start unit located in Plant XNP would provide the start-up power supply to the 3rd non-black-start unit located in Plant GZP through the black-start path XNP → BJ → LY → GZP. If the 3rd scheme fails to be carried out due to any reasons, the 12th scheme could be implemented.

To investigate the impacts of the interactions among indexes on the selection result of the optimal black-start scheme, the scenario without considering these interactions is carried out as well, by setting all the terms associated with interactions $\tau_{i\cap j}$ to be zero, and the group decision-making appraisal values in this scenario are also listed in Table 6 as denoted by VWOI. The order of VWOI shows significantly different results with that of VWI, and this demonstrates the significant impact of the interactions on the black-start decision-making result.

From the case studies with and without taking into account of the interactions among indexes, it can be seen that different merit orders of the black-start schemes are obtained, and most importantly the most preferred scheme is different under these two scenarios. Thus, it appears very demanding to carefully study the interactions among evaluating indices.

When the above decision-making process is completed, the black-start schemes such obtained should be revisited by the dispatchers. The charged power plants and substations in the restoration process can be regarded as "the black-start units" because these power plants and substations can provide the start-up power to those non-black-start units not yet restarted. For example, suppose that the 3rd scheme is employed in the first decision-making process. Thus, some substations such as BJ and LY, and the power plant GZP are charged, so these substations and the power plant GZP can be regarded as "black-start units". Then, the other 20 black-start schemes can be redefined, such as BJ → GT → JC → BHP, BJ → CH → SG → TP → TPP, LY → XCP. It can be concluded that the new black-start schemes and the data of indices such as the number of switching operations along the restoration paths are different from those in the first decision-making process. Hence, the presented decision-making method can be employed to evaluate the new black-start schemes as well. This process will be repeated until all non-black-start units are restarted. Finally, the whole restoration sequence can then be obtained.

5. Conclusions

The vague set theory based black-start decision-making approach is developed for optimizing the power system restoration procedure in this work. The proposed method is based on a group decision-making model, and could better model the practical decision-making procedure. In the developed method, the interactions among various indices could be taken into account, and the vague set can better model fuzzy information than existing methods. It is demonstrated by case studies that the interactions among various indices could have significant impacts on the evaluation results of the black-start schemes, and hence cannot be overlooked.

Acknowledgements

This work is supported by the Doctoral Fund of Ministry of Education of China (200805610020), China Postdoctoral Science Foundation Funded Project (20090461352, 201104712) and National Nature Science Foundation of China (51007080).

References

[1] Adibi MM, Clelland P, Fink L, Happ H, Kafka R, Raine J, et al. Power system restoration: a task force report. IEEE Trans Power Syst 1987;2(4):927–33.
[2] Adibi MM, Kafkal RJ, Milanicz DP. Expert system requirements for power system restoration. IEEE Trans Power Syst 1994;9(3):1592–8.
[3] Kirschen DS, Volkmann TL. Guiding a power system restoration with an expert system. IEEE Trans Power Syst 1991;6(2):558–88.
[4] Carvalho PMS, Ferreira LAFM, Barruncho LMF. Optimization approach to dynamic restoration of distribution systems. Int J Electr Power Energy Syst 2007;29(3):222–9.
[5] Joglekar JJ, Nerkar YP. A different approach in system restoration with special consideration of islanding schemes. Int J Electr Power Energy Syst 2008;30(9):519–24.
[6] Lin ZZ, Wen FS, Huang JS, Zhou H. Evaluation of black-start schemes employing entropy weight-based decision-making theory. J Energy Eng 2010;136(2):42–9.
[7] Zhang ZY, Chen YP. Optimization of power system black-start schemes based on the fuzzy multiple attributes decision-making method. High Volt Eng 2007;33(3):42–5. 52.
[8] Berredo RC, Ekel PY, Martini JSC, Palhares RM, Parreiras RO, Pereira JG. Decision making in fuzzy environment and multicriteria power engineering problems. Int J Electr Power Energy Syst 2011;33(3):623–32.
[9] Zhou XG, Tan CQ, Zhang Q. Vague set based decision-making theory and method. Beijing: Science Press; 2009.
[10] Islam S, Chowdhury N. A case-based windows graphic package for the education and training of power system restoration. IEEE Trans Power Syst 2001;16(2):181–7.
[11] Wu Y, Fang XY, Yan Z. Optimal power grid black start using fuzzy logic and expert system. Eur Trans Electr Power 2009;19(7):969–77.
[12] Lin ZZ, Wen FS, Xue YS, Zhou H. Black-start decision-making in smart grids using multi-attribute group eigenvalue method. Autom Electr Power Syst 2010;34(5):18–23.
[13] Vemuri BC, Malladi R. Intrinsic parameters for surface representation using deformable models. IEEE Trans Syst Man Cybernetics 1993;23(2):610–4.
[14] Ban AI. Intuitionistic fuzzy-valued fuzzy measures. In: Proceedings of second IEEE international conference on intelligent systems, Varna, Bulgaria; 2004. p. 427–9.
[15] Kojadinovic I. Modeling interaction phenomena using fuzzy measures: on the notions of interaction and independence. Fuzzy Sets Syst 2003;135(3):317–40.
[16] Feltes JW, Grande-Moran C. Black start studies for system restoration. In: Proceedings of IEEE power and energy society general meeting, Pittsburgh, Pennsylvania, USA; 2008. p. 1–8.
[17] Kojima Y, Wrashina S, Kato M, Watanabe H. The development of power system restoration method for a bulk power system by applying knowledge engineering techniques. IEEE Trans Power Syst 1989;4(3):1228–35.
[18] Hideaki T, Shigeyuki T, Daiki Y, Takahide N, Ryuichi Y. Multiple criteria assessment of substation conditions by pair-wise comparison of analytic hierarchy process. IEEE Trans Power Deliv 2010;25(4):3017–23.
[19] Baghaee HR, Abedi M. Calculation of weighting factors of static security indices used in contingency ranking of power systems based on fuzzy logic and analytical hierarchy process. Int J Electr Power Energy Syst 2011;33(4):855–60.

Please cite this article in press as: Zeng S et al. A new approach for power system black-start decision-making with vague set theory. Int J Electr Power Energ Syst (2011), doi:10.1016/j.ijepes.2011.09.012