

# Cloud-Data Envelopment Analysis Method Used for Assessment of Restoration Building Block Schemes

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**Abstract**—The selection of an optimized restoration building block (RBB) scheme among all available schemes is one of the most important factors impacting the power system restoration process after a complete or partial blackout. This paper presents a data envelopment analysis (DEA) model used as an empirical method to assess the RBB schemes. An  $N$ -level evaluation scale cloud system is built based on cloud theory to transform qualitative I/O indices of DEA model into quantitative values. Through joint utilization of the CCR (Charnes, Cooper and Rhodes) model and the LJK (Li, Jahanshahloo and Khodabakhshi) model, the established Joint-DEA model makes the newly proposed Cloud-DEA method a more feasible and robust method in assessment of RBB schemes.

**Index Terms**—Assessment model, cloud theory, data envelopment analysis (DEA), restoration building block (RBB) schemes.

## I. INTRODUCTION

MODERN society has come to depend on reliable electricity as an essential resource for national security, health and welfare, communications, finance, transportation, and food and water supply—in short, nearly all aspects of modern life. As the need for electricity increases, power system operations and maintenance become even more complex, with power systems often reaching their limits, leading to very high risks for large-area blackouts (e.g., August 14, 2003 Blackout in the United States and Canada [1]). After large-scale power failures, an urgent problem is to develop detailed plans and procedures for restoring power services safely, efficiently, and as expeditiously as possible [2].

Generally, the restoration process of a power system comprises three temporal stages: planning for restart, reintegration, and restoration of the bulk power supply [3]. A restoration building block (RBB) is a minimal configuration of an autonomous stable source of power, together with any necessary associated transmission, adequate to serve as a member of a set of one or more such subsystems that collectively are sufficient to reconstitute the bulk power system [4]. In the first stage of

the restoration process, RBBs are formulated by establishing energized restoration paths to provide power for cranking up non-black start units. Subsystems developed with one or more RBBs will be resynchronized in the following stage of the restoration process.

Since the modern power system is very complex, for a specific black start power or non-black start unit, there are many different RBB schemes available that are able to meet both the topological and technical specifications. Selecting an optimized RBB scheme, however, from all available schemes can significantly reduce the total restoration duration, thereby making it one of the most important factors impacting the power system restoration process after a complete or partial blackout [5].

To construct assessment models of RBB schemes, the data envelopment analysis (DEA) method is introduced in [6] and [7]. In these works, RBB schemes are treated as decision-making units (DMUs) in the DEA model. Efficiency scores of candidate RBB schemes are calculated by standard DEA models. Efficient RBB schemes are identified with efficiency scores equal to 1. However, the efficient RBB schemes are not comparable among themselves in standard DEA models. In [8], an initial super efficiency-data envelopment analysis (SE-DEA) model is introduced to rank efficient RBB schemes. This type of SE-DEA model is shown to experience problems of infeasibility [9], [10].

In this paper, an  $N$ -level evaluation scale cloud system is built up based on cloud theory to transform qualitative I/O indices of DEA models to quantitative values. A Joint-DEA model constructed by joint utilization of the CCR model and the LJK model is used to rank all candidate RBB schemes while overcoming the feasibility problem existing in the initial SE-DEA model. Based on the established  $N$ -level evaluation scale cloud system and the Joint-DEA model, the Cloud-DEA method is proposed as a more feasible and robust method to assess RBB schemes.

## II. JOINT-DEA MODEL

Data envelopment analysis, proposed and developed by Charnes, is a non-parametric technique that can be used to measure the relative efficiency of operating units with the same general goals and objectives [11]. DEA can separate the efficient operating units (firms, organizations, managers, schemes, etc.) from the inefficient ones on the basis of whether they lie on the efficient frontier spanned by the best units in a data set [12].

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Assume that there are  $n$  DMUs to be assessed. Each DMU consumes varying amounts of  $m$  different inputs to produce  $s$  different outputs. Specifically, DMU $_j$  consumes amounts  $\mathbf{X}_j = (x_{1j}, x_{2j}, \dots, x_{mj})$  of inputs and produces amounts  $\mathbf{Y}_j = (y_{1j}, y_{2j}, \dots, y_{sj})$  of outputs. The  $m \times n$  matrix of input measures is denoted by  $\mathbf{X}$ , and the  $s \times n$  matrix of output measures is denoted by  $\mathbf{Y}$ .

TABLE I  
INPUTS AND OUTPUTS OF DMUS

DMUs	Inputs $\mathbf{X}$				Outputs $\mathbf{Y}$			
DMU $_1$	$x_{11}$	$x_{21}$	$\dots$	$x_{m1}$	$y_{11}$	$y_{21}$	$\dots$	$y_{s1}$
DMU $_2$	$x_{12}$	$x_{22}$	$\dots$	$x_{m2}$	$y_{12}$	$y_{22}$	$\dots$	$y_{s2}$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
DMU $_j$	$x_{1j}$	$x_{2j}$	$\dots$	$x_{mj}$	$y_{1j}$	$y_{2j}$	$\dots$	$y_{sj}$
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
DMU $_n$	$x_{1n}$	$x_{2n}$	$\dots$	$x_{mn}$	$y_{1n}$	$y_{2n}$	$\dots$	$y_{sn}$

The CCR model [11], one of the most popular standard DEA models, and can be expressed as:

$$\left\{ \begin{array}{l} \min E_{j_0}^{-1} = \sum_{i=1}^m \omega_i x_{ij_0} \\ \text{s.t.} \quad \sum_{i=1}^m \omega_i x_{ij} \geq \sum_{r=1}^s \mu_r y_{rj} \quad j = 1, 2, \dots, n \\ \sum_{r=1}^s \mu_r y_{rj_0} = 1 \\ \omega_i, \mu_r \geq 0 \quad \forall i, r \end{array} \right. \quad (1)$$

where  $\omega_i$  and  $\mu_r$  are the weights of  $i^{\text{th}}$  input and  $r^{\text{th}}$  output respectively;  $E_{j_0}$  is the efficiency score (ES) of the  $j_0^{\text{th}}$  DMU under assessment. Each  $E_j \leq 1$ , if  $E_j = 1$ ; the DMU $_j$  is defined as the DEA efficient DMU.

The objective of a DEA model is to evaluate overall efficiencies of DMUs. Efficient DMUs are identified by ES equal to 1, and inefficient ones by ES less than 1. The efficient DMUs cannot be compared among themselves in the CCR or other standard DEA models. The initial SE-DEA model, developed in 1993 by Andersen and Petersen [13], is used to rank efficient DMUs in data envelopment analysis.

The initially proposed super efficiency model involves executing the standard DEA models, but under the assumption that the DMU under evaluation is excluded from the reference set. Initial SE-DEA model extended by CCR model can be described as below [13]:

$$\left\{ \begin{array}{l} \min E_{j_0}^{-1} = \sum_{i=1}^m \omega_i x_{ij_0} \\ \text{s.t.} \quad \sum_{i=1}^m \omega_i x_{ij} \geq \sum_{r=1}^s \mu_r y_{rj} \quad j = 1, 2, \dots, n \quad j \neq j_0 \\ \sum_{r=1}^s \mu_r y_{rj_0} = 1 \\ \omega_i, \mu_r \geq 0 \quad \forall i, r \end{array} \right. \quad (2)$$

New efficiency scores of DMUs are calculated by solving the initial SE-DEA model in order to rank efficient DMUs. But the drawback of the initially proposed super efficiency model is that it can be either stable or feasible when some inputs are close to zero [9]. Moreover, when the constant-return-to-scale

DEA models are used, it can result in infeasibility in the super efficiency evaluation, if and only if there is a zero in the data [10].

To overcome the drawbacks of initially proposed super efficiency models, a new super efficiency model called LJK model, while proposed in [14], is introduced in this paper to further rank DEA efficient DMUs identified by the standard DEA model. The LJK model can be written as:

$$\left\{ \begin{array}{l} \min E_{j_0} = 1 + \frac{1}{m} \sum_{i=1}^m \frac{s_{i2}^+}{R_i^-} \\ \text{s.t.} \quad \sum_{\substack{j=1 \\ j \neq j_0}}^n \lambda_j x_{ij} + s_{i1}^- - s_{i2}^+ = x_{ij_0} \quad i = 1, 2, \dots, m \\ \sum_{\substack{j=1 \\ j \neq j_0}}^n \lambda_j y_{rj} - s_r^+ = y_{rj_0} \quad r = 1, 2, \dots, m \\ R_i^- = \max_j(x_{ij}) \\ \lambda_j, s_{i1}^-, s_{i2}^+, s_r^+ \geq 0 \quad \forall i, j, r \end{array} \right. \quad (3)$$

where  $\lambda_j$  is weight of DMU $_j$ ;  $R_i^-$  is maximum of all  $i^{\text{th}}$  inputs of all evaluating DMUs; and  $s_{i1}^-$ ,  $s_{i2}^+$  and  $s_r^+$  are all slack variables.

The Joint-DEA model is built up by joint utilization of the CCR and LJK models in order to feasibly, and at the same time, robustly rank all DMUs in the data envelopment analysis. In the Joint-DEA model, the CCR model calculates all DMU efficiency scores first; then the LJK model calculates the efficiency scores of DEA efficient DMUs for further ranking. A higher efficiency score of a DMU means more efficiency compared to other DMUs.

### III. ASSESSMENT MODEL OF RBB SCHEMES

#### A. Assessment Factors of RBB Schemes

For candidate RBB schemes, there are several factors to consider, as described next:

1) Cranking power is delivered to non-black start units by associated restoration paths in the RBB. During this stage, energized high voltage lines may incur sustained power frequency overvoltage, switching transients, and harmonic resonance. A sustained overvoltage may overexcite transformers, generate harmonic distortions and overheating, and may also cause generator under-excitation, or even self-excitation and instability [15]. RBB schemes with shorter restoration paths and less voltage level changes may have priorities to be chosen.

2) Satisfied RBB schemes should include a non-black start unit with a large capacity on the condition that the capacity of crank power is sufficient [6]. The capacity of the generating units will determine the amount of load that can be energized [16]. The urgent degree of the load restoration should also be taken into account in assessment of RBB schemes [17].

3) The risk of implementation of the restoration path depends on the probability of successful changeover of individual breaker or isolator and increases with increased number of switching equipment involved in the restoration path [18]. Increased number of switching equipment also increases the time needed to formulate RBB in the first stage of the system

restoration process. It is reasonable, therefore, to construct RBB with fewer switching operations.

4) The starting priority of thermal units is another crucial factor to consider in RBB schemes. Depending on the unit's prior reservation time, a thermal unit manufacturer usually provides data for three types of unit start-up modes, namely, hot, warm, and cold [19]. A unit with a hot start-up mode has a high priority status for starting, due to a shorter start-up time, while a warm start-up mode is medium priority, and a cold start-up mode a low priority.

5) Finally, the technical feasibility of RBB schemes should be verified. Those RBB schemes that do not meet technical feasibility due to serious overvoltage, generator self-excitation, and so on should be eliminated from the candidate set of RBB schemes [20].

### B. Determination of the I/O Indices for the DEA Model

In order to use the DEA model to assess candidate RBB schemes, depending on the target of minimizing input indices and maximizing output indices, the I/O indices used in the DEA model are defined as detailed in Table II [6], [7]. According to main factors for candidate RBB schemes, number of voltage level change, length of restoration paths, frequency of switching operations and starting priority of non-black start unit make up the input indices. The output indices consist of capacity of non-black start unit and urgent degree of load restoration.

TABLE II  
INPUT AND OUTPUT INDICES USED IN DEA MODEL

Index Class	No.	Meaning of Index
Input	A	Number of voltage level change
	B	Length of restoration paths
	C	Frequency of switching operations
	D	Starting priority of non-black start unit
Output	E	Capacity of non-black start unit
	F	Urgent degree of load restoration

In the assessment of RBB schemes using the DEA method, each candidate RBB scheme is treated as a DMU of the DEA model. If input and output indices of candidate RBB schemes are assigned, RBB scheme efficiency scores can be accordingly calculated. A high efficiency score means the corresponding RBB scheme is a better scheme.

## IV. CLOUD-DEA METHOD FOR ASSESSMENT OF RBB SCHEMES

To assess RBB schemes with efficiency scores calculated by the DEA model, qualitative I/O indices in the DEA model (e.g., Index D and F in Table II) must be transformed to quantitative values. Cloud theory, an innovative and development of membership function in fuzzy theory, is a model of the uncertainty transformation between quantitative representation and qualitative concept using language value [21], [22]. Cloud theory is used to build an  $N$ -level evaluation scale cloud system to process qualitative I/O indices of the DEA model. Based on this, the Cloud-DEA method for assessment of RBB schemes is constructed.

### A. Basic Concepts of Cloud Theory

Let  $U$  be a universal set described by precise numbers, and  $C$  be the qualitative concept related to  $U$ . If there is a number  $x \in U$ , which randomly realizes the concept  $C$ , then the certainty degree of  $x$  for  $C$ , i.e.,  $\mu(x) \in [0, 1]$ , is a random value with stabilization tendency.

$$\mu : U \rightarrow [0, 1] \quad \forall x \in U \quad x \rightarrow \mu(x) \quad (4)$$

The distribution of  $x$  on  $U$  is thus defined as a cloud, and every  $x$  is defined as a cloud drop [23].

The cloud has the following properties [23]:

- 1) The random realization in the definition is the realization in terms of probability. The certainty degree is the membership degree in the fuzzy set, which also has the distribution of probability. All these statements show the correlation of fuzziness and randomness.
- 2) For any  $x \in U$ , the mapping from  $x$  to  $[0, 1]$  is multiple. The certainty degree of  $x$  on  $C$  is a probability distribution rather than a fixed number.
- 3) The cloud is composed of cloud drops and a cloud drop is the implementation of the qualitative concept once. The more cloud drops there are, the better the representation of the overall features of this concept.
- 4) The more probable the cloud drop appears, the higher the certainty degree, and hence the more contribution the cloud drop makes to the concept.

Normal distribution is one of the most important distributions in probability theory. In a cloud model, if  $x$  is accorded with a normal distribution  $N(E_x, E'_n)$ , where  $E'_n$  is with  $N(E_n, H_e)$ , the certainty degree of  $x$  on  $C$  is

$$\mu(x) = e^{-\frac{(x-E_x)^2}{2(E'_n)^2}} \quad (5)$$

Then the distribution of  $x$  on  $U$  is a normal cloud recorded as  $C(E_x, E_n, H_e)$ . Expectation  $E_x$  is the mathematical expectation of the cloud drop, determining the center of the cloud; Entropy  $E_n$  determines the range of the cloud, reflecting the dispersing extent of the cloud drops; Hyper-entropy  $H_e$  is the uncertainty measurement of the entropy.

If three parameters ( $E_x, E_n$  and  $H_e$ ) are given, cloud drops  $\mathbf{Drop}(x_i, \mu_i)$  can be generated through following steps:

*Step 1:* Generate a normally distributed random number  $E'_{ni}$  with expectation  $E_n$  and standard deviation  $H_e$ , i.e.,  $E'_{ni} = \text{random}N(E_n, H_e)$ .

*Step 2:* Generate a normally distributed random number  $x_i$  with expectation  $E_x$  and standard deviation  $E'_{ni}$ , i.e.,  $x_i = \text{random}N(E_x, E'_{ni})$ .

*Step 3:* Calculate  $\mu_i = e^{-\frac{(x_i-E_x)^2}{2(E'_{ni})^2}}$ .

*Step 4:*  $x_i$  with certainty degree of  $\mu_i$  is a cloud drop  $\mathbf{Drop}(x_i, \mu_i)$  in the domain.

*Step 5:* Repeat steps 1 to 4 until  $n$  cloud drops are generated.

For example, Fig. 1 schematically shows a normal cloud with 1000 cloud drops generated by a normal cloud model.

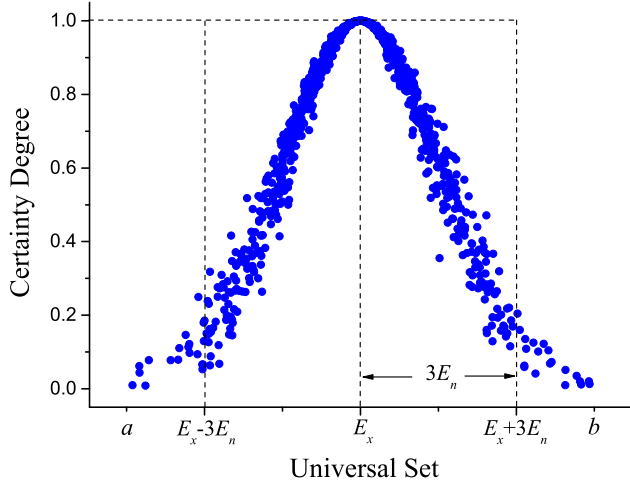


Fig. 1. Normal cloud with 1000 cloud drops.

### B. Processing of Qualitative I/O Indices of DEA Model Using Cloud Theory

For a certain qualitative I/O index of DEA model, assume that a total of  $N$  qualitative importance degree concepts can be selected to represent the degree of importance of the qualitative index value of a candidate RBB scheme. Cloud theory is used to transform every qualitative importance degree concept to a normal cloud. Relevant  $N$  normal clouds then make up the  $N$ -level evaluation scale cloud system. The steps to determine the parameters of normal clouds of an  $N$ -level evaluation scale cloud system are presented below.

Suppose  $U_i$  is the universal set described by precise numbers of the  $i^{\text{th}}$  normal cloud of the  $N$ -level evaluation scale cloud system that corresponds to the  $i^{\text{th}}$  qualitative importance degree concept. And the universal set described by precise numbers of the  $N$ -level evaluation scale cloud system is

$$U_N = \bigcup_{i=1}^N U_i \quad (6)$$

Assume that the interval length of the center of adjacent normal clouds is the same and the measure of all  $U_i$  ( $i = 1, 2, \dots, N$ ) is identical. Deem  $U_N = [a, b]$  ( $a = 0, b > 0$  in general), the interval length  $d$  of the center of adjacent normal clouds and the expectation  $E_{xi}$  of  $i^{\text{th}}$  normal cloud of  $N$ -level evaluation scale cloud system are described in (7) and (8).

$$d = \frac{b - a}{N} \quad (7)$$

$$E_{xi} = a + \frac{2i - 1}{2}d \quad i = 1, 2, \dots, N \quad (8)$$

According to [23] and as schematically shown in Fig. 1, cloud drops generated by normal cloud models located within  $[E_x - 3E_n, E_x + 3E_n]$  take up 99.74% of the whole quantity. Cloud drops out of  $[E_x - 3E_n, E_x + 3E_n]$  can be neglected due to “the  $3E_n$ ” rule of the normal cloud model. Golden section, which is a number that satisfies the equation  $r^2 = 1 - r$  and has been known to elicit more pleasure than any other ratio, has been utilized as an optimization approach for

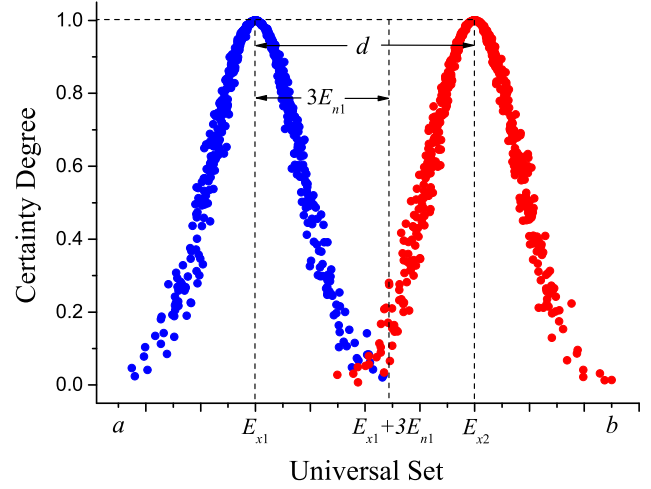


Fig. 2. Two adjacent normal clouds of the  $N$ -level evaluation scale cloud system.

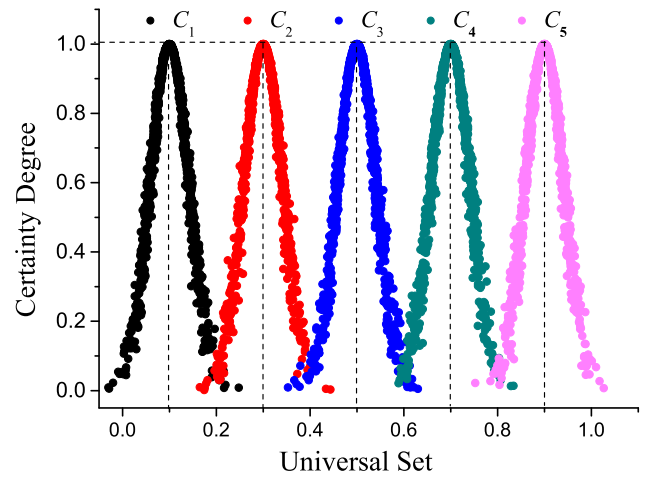


Fig. 3. Five-level evaluation scale cloud system.

solving actual scientific, technical, and engineering problems [24], [25]. As schematically shown in Fig. 2, golden section is introduced to determine the entropy  $E_n$  of normal clouds in the  $N$ -level evaluation scale cloud system. Entropy  $E_{ni}$  of the  $i^{\text{th}}$  normal cloud of the  $N$ -level evaluation scale cloud system can be calculated using (9).

$$(3E_{ni})^2 = d(d - 3E_{ni}) \quad i = 1, 2, \dots, N \quad (9)$$

Generally, hyper-entropy  $H_e$  is related to  $E_n$ . An approximate linear relationship with coefficient  $k$  (i.e.,  $k = 0.1$ ) is used to calculate  $H_e$  of normal clouds in the  $N$ -level evaluation scale cloud system.  $H_{ei}$  of  $i^{\text{th}}$  normal cloud of the  $N$ -level evaluation scale cloud system is expressed in (10).

$$H_{ei} = kE_{ni} \quad i = 1, 2, \dots, N \quad (10)$$

After all the three parameters ( $E_x$ ,  $E_n$  and  $H_e$ ) of the normal clouds are given, qualitative I/O indices of candidate RBB schemes can be transformed to quantitative values by the generation of cloud drops by normal clouds in corresponding  $N$ -level evaluation scale cloud systems.

TABLE III  
PARAMETERS OF NORMAL CLOUDS IN THE FIVE-LEVEL EVALUATION SCALE CLOUD SYSTEM

Level No.	Normal Cloud Parameters
1	$C_1(0.1, 0.0412, 0.0041)$
2	$C_2(0.3, 0.0412, 0.0041)$
3	$C_3(0.5, 0.0412, 0.0041)$
4	$C_4(0.7, 0.0412, 0.0041)$
5	$C_5(0.9, 0.0412, 0.0041)$

For example, given  $N = 5$  and  $U_N = [0, 1]$ , the five-level evaluation scale cloud system is shown in Fig. 3 with parameters of 5 normal clouds in Table III.

### C. Major Steps of Cloud-DEA Method

Based on the involvement of I/O indices in the assessment model of RBB schemes, the Cloud-DEA method for calculating efficiency scores of RBB schemes is constructed as follows:

- 1) transform qualitative I/O indices to quantitative values using corresponding  $N$ -level evaluation scale cloud systems;
- 2) calculate efficiency scores of candidate RBB schemes through the Joint-DEA model.

In order to more accurately represent the randomness and fuzziness of qualitative I/O indices, efficiency scores of  $n$  candidate RBB schemes are calculated repeatedly by Cloud-DEA model (e.g., recalculated  $m$  times). The mean efficiency score of  $i^{\text{th}}$  RBB scheme is shown as:

$$\bar{h}_i = \frac{1}{m} \sum_{j=1}^m h_{ij} \quad i = 1, 2, \dots, n \quad (11)$$

where  $h_{ij}$  is the efficiency score of the  $i^{\text{th}}$  RBB scheme calculated in the  $j^{\text{th}}$  time.

After the mean efficiency scores of candidate RBB schemes are calculated, the schemes can then be ranked by mean efficiency scores. An RBB scheme with a higher mean efficiency score means that it is more efficient when compared to other schemes.

## V. CASE STUDY

In this section, a savnw 23-bus system is used to study the validity of the Cloud-DEA method used in assessment of RBB schemes. The savnw 23-bus system consists of 6 units, 23 transmission branches and 11 transformer branches with system parameters referring to PSS/E University 33.

Fig. 4 is the network structure of the savnw 23-bus system. A unit name is expressed in terms of the bus number it connects with. Note that unit 3018 with a maximal power of 117 MW is the black start power of the system. Candidate RBB schemes are listed in Table IV with target non-black start unit and restoration paths involved in each RBB scheme.

For candidate RBB schemes of the savnw 23-bus system, their I/O indices data are described in Table V. The sum of reactance (per unit value) of transmission lines is used to represent the length of restoration paths. For qualitative I/O indices, the corresponding qualitative importance degree sets of index D and F are high, middle, low and not urgent, not too

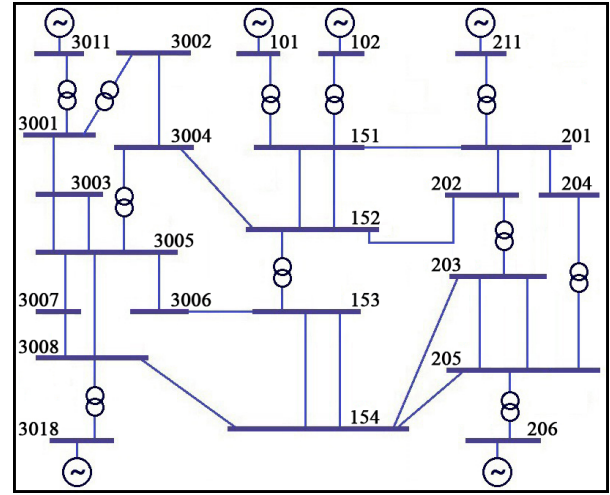


Fig. 4. Network structure of the savnw 23-bus system.

TABLE VI  
THREE-LEVEL EVALUATION SCALE CLOUD SYSTEM OF INDEX D

Level No.	Index Value	Normal Cloud Parameters
1	High	$C_1(0.1667, 0.0687, 0.0069)$
2	Middle	$C_2(0.5000, 0.0687, 0.0069)$
3	Low	$C_3(0.8333, 0.0687, 0.0069)$

TABLE VII  
FIVE-LEVEL EVALUATION SCALE CLOUD SYSTEM OF INDEX F

Level No.	Index Value	Normal Cloud Parameters
1	Not urgent	$C_1(0.1, 0.0412, 0.0041)$
2	Not too urgent	$C_2(0.3, 0.0412, 0.0041)$
3	Normally urgent	$C_3(0.5, 0.0412, 0.0041)$
4	Quite urgent	$C_4(0.7, 0.0412, 0.0041)$
5	Very urgent	$C_5(0.9, 0.0412, 0.0041)$

urgent, normally urgent, quite urgent, very urgent respectively. Set  $U_N = [0, 1]$ . The three-level evaluation scale cloud system and the five-level evaluation scale cloud system are established in Table VI and VII to transform qualitative data of indices D and F to quantitative values.

Assume that efficiency scores of candidate RBB schemes are calculated repeatedly 10 times by the Cloud-DEA model; the corresponding 10 groups of quantitative I/O index data are listed in the Appendix (Table AI–AX), and the efficiency scores with mean values are stored in Table VIII. According to the solutions in Table VIII, Scheme 3 with the highest mean efficiency score is selected as the optimized RBB scheme.

In Table IX, there is a group of quantitative I/O indices data generated by evaluation scale cloud systems with an input index value close to zero (index D of Scheme 1) for a comparison test. Efficiency scores calculated by different DEA models are shown in Table X. It can be found that the efficiency score of Scheme 1 under the initial SE-DEA model is far more than other schemes. Suppose that the index D value of Scheme 1 meets a small disturbance (from 0.0008 to 0.0007, shown in Table XI) and RBB Scheme efficiency scores are recalculated and stored in Table XII.

TABLE IV  
CANDIDATE RBB SCHEMES OF THE SAVNW 23-BUS SYSTEM

Scheme No.	Black Start Power	Non-Black Start Unit	Restoration Paths
1	3018	101	3018→3008→154→153→152→151→101
2	3018	102	3018→3008→154→153→152→151→102
3	3018	206	3018→3008→154→205→206
4	3018	211	3018→3008→154→205→204→201→211
5	3018	3011	3018→3008→3005→3003→3001→3011
6	3018	101	3018→3008→3005→3004→152→151→101
7	3018	101	3018→3008→154→203→202→201→151→101
8	3018	101	3018→3008→154→203→202→201→151→101
9	3018	101	3018→3008→154→205→204→201→151→101

TABLE V  
I/O INDICES DATA OF CANDIDATE RBB SCHEMES

Scheme No.	A (times)	B (p.u.)	C (times)	D	E (MW)	F
1	3	0.2256	21	High	810	Not too urgent
2	3	0.2256	21	Middle	810	Not too urgent
3	2	0.1237	14	Middle	900	Very urgent
4	3	0.1766	21	Low	616	Quite urgent
5	2	0.2070	17	Middle	900	Not urgent
6	3	0.2408	21	High	810	Not urgent
7	3	0.2328	24	High	810	Normally urgent
8	3	0.2168	24	High	810	Quite urgent
9	3	0.1839	24	High	810	Very urgent

TABLE VIII  
EFFICIENCY SCORES OF CANDIDATE RBB SCHEMES CALCULATED BY CLOUD-DEA MODEL

Scheme No.	$h_{i1}$	$h_{i2}$	$h_{i3}$	$h_{i4}$	$h_{i5}$	$h_{i6}$	$h_{i7}$	$h_{i8}$	$h_{i9}$	$h_{i10}$	$\bar{h}_i$
1	0.8743	0.9120	1.0289	0.9703	0.9947	0.8866	0.9222	1.0702	0.9520	1.0102	0.9621
2	0.7280	0.7132	0.6621	0.6347	0.7069	0.6529	0.7086	0.6970	0.7417	0.7221	0.6967
3	1.3005	1.3151	1.2838	1.3181	1.2909	1.2827	1.2928	1.2968	1.2813	1.3040	1.2966
4	0.5550	0.5219	0.5742	0.5625	0.5530	0.6329	0.5194	0.5799	0.5602	0.4922	0.5551
5	1.0206	1.0021	1.0203	1.0097	1.0351	1.0031	1.0210	1.0084	1.0049	1.0152	1.0140
6	1.0283	1.0140	0.8524	0.8906	1.0142	0.9992	1.0387	0.8591	0.8747	0.9807	0.9552
7	1.0012	1.0085	0.9190	0.9347	0.9584	0.9024	0.9435	0.8675	0.9317	0.9122	0.9379
8	0.9905	0.9977	0.9223	0.9736	0.9314	1.0337	1.0045	0.9525	1.0226	1.0128	0.9842
9	1.0698	1.0578	1.0931	1.0226	1.0821	1.0561	1.0759	1.0797	1.0896	1.0784	1.0705

TABLE IX  
QUANTITATIVE I/O INDEX DATA I FOR COMPARISON TEST

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.0008	810	0.3172
2	3	0.2256	21	0.5494	810	0.3136
3	2	0.1237	14	0.5305	900	0.9030
4	3	0.1766	21	0.7855	616	0.7634
5	2	0.2070	17	0.5119	900	0.0933
6	3	0.2408	21	0.1851	810	0.0873
7	3	0.2328	24	0.1111	810	0.5537
8	3	0.2168	24	0.2582	810	0.7069
9	3	0.1839	24	0.1483	810	0.8252

TABLE X  
COMPARISON TEST RESULTS OF QUANTITATIVE I/O INDEX DATA I

Scheme No.	CCR	Initial SE-DEA	LJK	Joint-DEA
1	1.0000	138.8750	1.0617	1.0617
2	0.6849	0.6849	1.0000	0.6849
3	1.0000	1.8931	1.3232	1.3232
4	0.5922	0.5922	1.0000	0.5922
5	1.0000	1.0142	1.0039	1.0039
6	0.8661	0.8661	1.0000	0.8661
7	0.9559	0.9559	1.0000	0.9559
8	0.8677	0.8677	1.0000	0.8677
9	1.0000	1.6006	1.0763	1.0763

A comparative analysis of the comparison test results of quantitative I/O index data I and II in Tables X and XII shows that the small disturbance of the index D value of Scheme 1

leads to a high fluctuation of the efficiency score of the scheme (from 138.8750 to 158.7143) under the initial SE-DEA model. This reveals the initial SE-DEA model is not stable when some

TABLE XI  
QUANTITATIVE I/O INDEX DATA II FOR COMPARISON TEST

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.0007	810	0.3172
2	3	0.2256	21	0.5494	810	0.3136
3	2	0.1237	14	0.5305	900	0.9030
4	3	0.1766	21	0.7855	616	0.7634
5	2	0.2070	17	0.5119	900	0.0933
6	3	0.2408	21	0.1851	810	0.0873
7	3	0.2328	24	0.1111	810	0.5537
8	3	0.2168	24	0.2582	810	0.7069
9	3	0.1839	24	0.1483	810	0.8252

TABLE XII  
COMPARISON TEST RESULTS OF QUANTITATIVE I/O INDEX DATA II

Scheme No.	CCR	Initial SE-DEA	LJK	Joint-DEA
1	1.0000	158.7143	1.0618	1.0618
2	0.6849	0.6849	1.0000	0.6849
3	1.0000	1.8931	1.3232	1.3232
4	0.5922	0.5922	1.0000	0.5922
5	1.0000	1.0142	1.0039	1.0039
6	0.8661	0.8661	1.0000	0.8661
7	0.9558	0.9558	1.0000	0.9558
8	0.8677	0.8677	1.0000	0.8677
9	1.0000	1.6006	1.0763	1.0763

inputs are close to zero.

To further demonstrate the feasibility and robustness of the Joint-DEA model, the index D of Scheme 1 in Table IX is extremely assigned to zero (shown in Table XIII). Efficiency scores under different DEA models are recalculated and listed in Table XIV. According to Table XIV, when the index D of Scheme 1 is extremely assigned to zero, the initial SE-DEA model is infeasible, while the Joint-DEA model keeps the robustness.

Besides SE-DEA models, among other established models that rank efficient DMUs, one typical approach is the integration of DEA models and TOPSIS (the technique for order preference by similarity to ideal solution) [26]–[28]. In [26], two virtual DMUs called ideal DMU (IDMU) and anti-ideal DMU (ADMU) are introduced for measuring the optimistic and pessimistic efficiencies of DMUs, and a relative closeness (RC) score, which is obtained by integration of the two efficiencies, and is used as the basis for ranking DMUs.

The method in [26] was later improved in [27] and [28]. In [27], the assessment of the worst possible relative efficiencies of ADMU and real DMUs was revised in order to provide a more logical method. The method in [27] produced a more consistent ranking result with the initial SE-DEA model. In [28], rescaling parameters were introduced to formulate a rescaled model to assess the worst possible relative efficiency and make the method in [26] more reassuring for use. As for different groups of I/O index data, the rescaling parameters needed in the model in [28] are changeable due to constraints. Established models in [26] and [27] are chosen for further comparison with the Joint-DEA model.

TABLE XIII  
QUANTITATIVE I/O INDEX DATA III FOR COMPARISON TEST

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0	810	0.3172
2	3	0.2256	21	0.5494	810	0.3136
3	2	0.1237	14	0.5305	900	0.9030
4	3	0.1766	21	0.7855	616	0.7634
5	2	0.2070	17	0.5119	900	0.0933
6	3	0.2408	21	0.1851	810	0.0873
7	3	0.2328	24	0.1111	810	0.5537
8	3	0.2168	24	0.2582	810	0.7069
9	3	0.1839	24	0.1483	810	0.8252

TABLE XIV  
COMPARISON TEST RESULTS OF QUANTITATIVE I/O INDEX DATA III

Scheme No.	CCR	Initial SE-DEA	LJK	Joint-DEA
1	1.0000	Infeasible	1.0620	1.0620
2	0.6848	0.6848	1.0000	0.6848
3	1.0000	1.8931	1.3232	1.3232
4	0.5922	0.5922	1.0000	0.5922
5	1.0000	1.0142	1.0039	1.0039
6	0.8657	0.8657	1.0000	0.8657
7	0.9554	0.9554	1.0000	0.9554
8	0.8675	0.8675	1.0000	0.8675
9	1.0000	1.6006	1.0763	1.0763

While using either model in [26] or [27] to test the 10 groups of quantitative I/O index data in assessment of RBB schemes listed in the Appendix (Table AI–AX), only 5 groups of data (data II, VI, VII, VIII, and IX) can be solved for the RC scores of RBB schemes. For the other 5 groups of data (data I, III, IV, V, and X), problems exist in the measuring of the optimistic efficiencies of DMUs due to no feasible solutions of corresponding linear programming problems, which show that the models in [26] and [27] are not stable in assessment of RBB schemes.

Take the quantitative I/O index data II (listed in Table AII) as an example. The RC scores and efficiency scores of RBB schemes calculated by different models with ranking results are shown in Table XV. Ranking results of both models in [26] and [27] lack consistency with the initial SE-DEA model. The comparison of the Joint-DEA model with the established models in [26] and [27], therefore, further validate the robustness of the Joint-DEA model.

## VI. CONCLUSIONS

In this paper, the Cloud-DEA method is proposed based on the  $N$ -level evaluation scale cloud system and the Joint-DEA model to assess the RBB schemes. Candidate RBB schemes are treated as DMUs in the DEA model. As efficiency scores of DMUs cannot be directly calculated when the DEA model contains qualitative I/O indices, the  $N$ -level evaluation scale cloud system based on cloud theory is built to transform qualitative I/O indices of the DEA model into quantitative values.

The initial SE-DEA model can be used to further rank the efficient DMUs identified by standard DEA models. But

TABLE XV  
COMPARISON TEST RESULTS OF QUANTITATIVE I/O INDEX DATA II IN ASSESSMENT OF RBB SCHEMES

Scheme No.	Model in [26]		Model in [27]		Joint-DEA		Initial SE-DEA	
	RC Score	Ranking	RC Score	Ranking	Efficiency Score	Ranking	Efficiency Score	Ranking
1	0.4304	6	0.3245	6	0.9120	7	0.9120	7
2	0.4067	7	0.2506	8	0.7132	8	0.7132	8
3	0.7769	1	0.3659	4	1.3151	1	1.8663	1
4	0.5641	5	0.1990	9	0.5219	9	0.5219	9
5	0.2245	9	0.3012	7	1.0021	5	1.0070	5
6	0.2333	8	0.3325	5	1.0140	3	1.0603	4
7	0.6544	4	0.4806	1	1.0085	4	1.3909	3
8	0.7061	3	0.4760	3	0.9977	6	0.9977	6
9	0.7717	2	0.4805	2	1.0578	2	1.4268	2

the initial SE-DEA model is confronted with the problem of infeasibility. By joint utilization of the CCR model and the LJK model, the Joint-DEA model is established to fully rank the DMUs while overcoming the feasibility problem existing in the initial SE-DEA model.

In the case study, the candidate RBB schemes of the savnw 23-bus system are assessed and optimized by the Cloud-DEA method. The comparison test results of the Joint-DEA model and other established models demonstrate the feasibility and robustness of the Joint-DEA model, which guarantee the newly proposed Cloud-DEA method as a more feasible and robust method in assessment of RBB schemes.

## APPENDIX

TABLE AI  
QUANTITATIVE I/O INDEX DATA I IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.2903	810	0.3535
2	3	0.2256	21	0.5309	810	0.3197
3	2	0.1237	14	0.5664	900	0.8786
4	3	0.1766	21	0.9963	616	0.6962
5	2	0.2070	17	0.4843	900	0.0975
6	3	0.2408	21	0.1247	810	0.0829
7	3	0.2328	24	0.1402	810	0.4704
8	3	0.2168	24	0.1622	810	0.6728
9	3	0.1839	24	0.1668	810	0.8916

TABLE AII  
QUANTITATIVE I/O INDEX DATA II IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.2257	810	0.3034
2	3	0.2256	21	0.5036	810	0.3062
3	2	0.1237	14	0.5011	900	0.9466
4	3	0.1766	21	0.8802	616	0.7053
5	2	0.2070	17	0.4933	900	0.1081
6	3	0.2408	21	0.1263	810	0.1036
7	3	0.2328	24	0.0770	810	0.4967
8	3	0.2168	24	0.1071	810	0.6432
9	3	0.1839	24	0.1536	810	0.8964

TABLE AIII  
QUANTITATIVE I/O INDEX DATA III IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.1073	810	0.2776
2	3	0.2256	21	0.5673	810	0.3272
3	2	0.1237	14	0.4722	900	0.8408
4	3	0.1766	21	0.8209	616	0.6892
5	2	0.2070	17	0.4055	900	0.1170
6	3	0.2408	21	0.2634	810	0.0779
7	3	0.2328	24	0.1798	810	0.4850
8	3	0.2168	24	0.1826	810	0.7072
9	3	0.1839	24	0.1228	810	0.9251

TABLE AIV  
QUANTITATIVE I/O INDEX DATA IV IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.2683	810	0.3153
2	3	0.2256	21	0.5466	810	0.2659
3	2	0.1237	14	0.3954	900	0.8760
4	3	0.1766	21	0.8025	616	0.7035
5	2	0.2070	17	0.3643	900	0.1328
6	3	0.2408	21	0.3154	810	0.1189
7	3	0.2328	24	0.2521	810	0.4663
8	3	0.2168	24	0.2299	810	0.7854
9	3	0.1839	24	0.2158	810	0.8173

TABLE AV  
QUANTITATIVE I/O INDEX DATA V IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.1811	810	0.2757
2	3	0.2256	21	0.5851	810	0.2983
3	2	0.1237	14	0.5726	900	0.8082
4	3	0.1766	21	0.8219	616	0.6381
5	2	0.2070	17	0.4388	900	0.1056
6	3	0.2408	21	0.1344	810	0.0354
7	3	0.2328	24	0.2025	810	0.5552
8	3	0.2168	24	0.2453	810	0.7572
9	3	0.1839	24	0.1866	810	0.8584



TABLE AVI  
QUANTITATIVE I/O INDEX DATA VI IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.2389	810	0.3549
2	3	0.2256	21	0.5961	810	0.2825
3	2	0.1237	14	0.4771	900	0.8238
4	3	0.1766	21	0.8930	616	0.7444
5	2	0.2070	17	0.4644	900	0.1322
6	3	0.2408	21	0.1264	810	0.0914
7	3	0.2328	24	0.1284	810	0.4720
8	3	0.2168	24	0.0172	810	0.7293
9	3	0.1839	24	0.1438	810	0.9076

TABLE AVII  
QUANTITATIVE I/O INDEX DATA VII IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.1693	810	0.3153
2	3	0.2256	21	0.5478	810	0.3202
3	2	0.1237	14	0.5750	900	0.8513
4	3	0.1766	21	0.8294	616	0.6312
5	2	0.2070	17	0.4747	900	0.1004
6	3	0.2408	21	0.0410	810	0.1331
7	3	0.2328	24	0.1561	810	0.4759
8	3	0.2168	24	0.1338	810	0.7368
9	3	0.1839	24	0.1772	810	0.8975

TABLE AVIII  
QUANTITATIVE I/O INDEX DATA VIII IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.0057	810	0.3030
2	3	0.2256	21	0.5377	810	0.2732
3	2	0.1237	14	0.5476	900	0.8523
4	3	0.1766	21	0.7782	616	0.7043
5	2	0.2070	17	0.5067	900	0.0078
6	3	0.2408	21	0.2063	810	0.1097
7	3	0.2328	24	0.2144	810	0.5077
8	3	0.2168	24	0.1745	810	0.6342
9	3	0.1839	24	0.2256	810	0.8944

TABLE AIX  
QUANTITATIVE I/O INDEX DATA IX IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.1910	810	0.2769
2	3	0.2256	21	0.4805	810	0.3133
3	2	0.1237	14	0.5266	900	0.8732
4	3	0.1766	21	0.9105	616	0.6983
5	2	0.2070	17	0.5046	900	0.1104
6	3	0.2408	21	0.2813	810	0.0935
7	3	0.2328	24	0.1054	810	0.5206
8	3	0.2168	24	0.0235	810	0.7046
9	3	0.1839	24	0.1062	810	0.9765

TABLE AX  
QUANTITATIVE I/O INDEX DATA X IN ASSESSMENT OF RBB SCHEMES

Scheme No.	A	B	C	D	E	F
1	3	0.2256	21	0.1222	810	0.2672
2	3	0.2256	21	0.5056	810	0.2793
3	2	0.1237	14	0.5243	900	0.9211
4	3	0.1766	21	0.8112	616	0.6472
5	2	0.2070	17	0.4655	900	0.0499
6	3	0.2408	21	0.1418	810	0.1088
7	3	0.2328	24	0.1769	810	0.4654
8	3	0.2168	24	0.0859	810	0.6754
9	3	0.1839	24	0.1305	810	0.9248

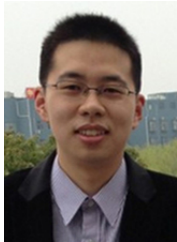
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REFERENCES

- [1] E. H. Allen, R. B. Stuart, and T. E. Wiedman, "No light in august: Power system restoration following the 2003 north american blackout," *IEEE Power and Energy Magazine*, vol. 12, no. 1, pp. 24–33, Jan 2014.
- [2] J. Feltes and C. Grande-Moran, "Down, but not out: A brief overview of restoration issues," *IEEE Power and Energy Magazine*, vol. 12, no. 1, pp. 34–43, Jan 2014.
- [3] M. Adibi, P. Clelland, L. Fink, H. Happ, R. Kafka, J. Raine, D. Scheurer, and F. Trefny, "Power system restoration—a task force report," *IEEE Transactions Power Systems*, vol. 2, no. 4, pp. 271–277, May 1987.
- [4] L. H. Fink, K. L. Liou, and C. C. Liu, "From generic restoration actions to specific restoration strategies," *IEEE Transactions Power Systems*, vol. 10, no. 2, pp. 745–752, May 1995.
- [5] A. A. Mota, L. T. M. Mota, and A. Morelato, "Restoration building blocks identification using a heuristic search approach," in *Proc. IEEE Power Engineering Society General Meeting*, 2006, pp. 1–7.
- [6] Y. Liu, X. Gu, and D. Zhang, "Data envelopment analysis based strategy of assessing schemes for power system black start," in *Proc. IEEE/PES Transmission and Distribution Conference and Exhibition: Asia and Pacific*, 2005, pp. 1–5.
- [7] Y. Wu, X. Fang, and Z. Yan, "Optimal power grid black start using fuzzy logic and expert system," *European Transactions on Electrical Power*, vol. 19, no. 7, pp. 969–977, 2009.
- [8] Y. Wu and X. Fang, "GSM based algorithm for decision-support expert system to assess black-start plans," in *Proc. Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, 2008. (DRPT)*, 2008, pp. 2339–2342.
- [9] R. M. Thrall, "Duality, classification and slacks in DEA," *Annals of Operations Research*, vol. 66, no. 2, pp. 109–138, 1996.
- [10] J. Zhu, "Robustness of the efficient DMUs in data envelopment analysis," *European Journal of operational research*, vol. 90, no. 3, pp. 451–460, 1996.
- [11] A. Charnes, W. Cooper, and E. Rhodes, "Measuring the efficiency of decision making units," *European journal of operational research*, vol. 2, no. 6, pp. 429–444, 1978.
- [12] K. W. Wöber, "Data envelopment analysis," *Journal of Travel & Tourism Marketing*, vol. 21, no. 4, pp. 91–108, 2007.
- [13] P. Andersen and N. C. Petersen, "A procedure for ranking efficient units in data envelopment analysis," *Management Science*, vol. 39, no. 10, pp. 1261–1264, 1993.
- [14] S. Li, G. R. Jahanshahloo, and M. Khodabakhshi, "A super-efficiency model for ranking efficient units in data envelopment analysis," *Applied Mathematics and Computation*, vol. 184, no. 2, pp. 638–648, 2007.
- [15] M. M. Adibi and L. H. Fink, "Power system restoration planning," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 22–28, Feb 1994.
- [16] S. Liu, Y. Hou, C. C. Liu, and R. Podmore, "The healing touch: Tools and challenges for smart grid restoration," *IEEE Power and Energy Magazine*, vol. 12, no. 1, pp. 54–63, Jan 2014.
- [17] W. Ye and X. Fang, "Data envelopment analysis based optimal fuzzy algorithm for assessing power grid black-start plans," *Transactions of China Electrotechnical Society*, vol. 23, no. 8, pp. 101–106, 2008.

- [18] S. Islam and N. Chowdhury, "A case-based windows graphic package for the education and training of power system restoration," *IEEE Transactions on Power Systems*, vol. 16, no. 2, pp. 181–187, May 2001.
- [19] C. K. Simoglou, P. N. Biskas, and A. G. Bakirtzis, "Optimal self-scheduling of a thermal producer in short-term electricity markets by MILP," *IEEE Transactions on Power Systems*, vol. 25, no. 4, pp. 1965–1977, Nov 2010.
- [20] Y. Gao, X. Gu, and Y. Liu, "Automatic derivation and assessment of power system black-start schemes," *Automation of Electric Power Systems*, vol. 28, no. 13, pp. 50–54, 2004.
- [21] D. Li, H. Meng, and X. Shi, "Membership clouds and membership cloud generators," *Journal of Computer Research and Development*, vol. 32, no. 6, pp. 15–20, 1995.
- [22] P. Lv, L. Yuan, and J. Zhang, "Cloud theory-based simulated annealing algorithm and application," *Engineering Applications of Artificial Intelligence*, vol. 22, no. 4, pp. 742–749, 2009.
- [23] D. Li and Y. Du, *Artificial Intelligence With Uncertainty*. Boca Raton, FL: CRC Press, 2007.
- [24] Y. Lu, "A golden section approach to optimization of automotive friction materials," *Journal of Materials Science*, vol. 38, no. 5, pp. 1081–1085, 2003.
- [25] J. Piehl, "The 'golden section': An artifact of stimulus range and demand characteristics," *Perceptual and Motor Skills*, vol. 43, no. 1, pp. 47–50, 1976.
- [26] Y. M. Wang and Y. Luo, "DEA efficiency assessment using ideal and anti-ideal decision making units," *Applied Mathematics and Computation*, vol. 173, no. 2, pp. 902–915, 2006.
- [27] D. Wu, "A note on DEA efficiency assessment using ideal point: an improvement of Wang and Luo's model," *Applied Mathematics and Computation*, vol. 183, no. 2, pp. 819–830, 2006.
- [28] J. X. Chen, "A comment on DEA efficiency assessment using ideal and anti-ideal decision making units," *Applied Mathematics and Computation*, vol. 219, no. 2, pp. 583–591, 2012.



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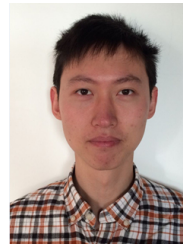
interests are in application of optimization theory to power systems and power markets, and dynamic security assessment.



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