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Black-start decision making based on collaborative filtering for power system restoration

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ABSTRACT

Black-start decision making plays an important role in power system restoration after a large-area blackout. The entropy method is one of the most popular methods for determining the weights of indexes in black-start decision making. In spite of its success, the entropy method is affected significantly by normalization methods, which makes the final evaluation results of black-start schemes not reliable. To address this issue, in this article, we propose a novel black-start decision making method based on collaborative filtering. In the proposed method, the values in the decision matrix are withheld, and the collaborative filtering technique is adopted to predict the withheld values. Based on the prediction values and true values, the MAE weights of all the indexes are obtained. Finally, the MAE weights are used to compute the overall assessment value of each black-start scheme. Based on the data of Guangdong power system of China, experiments were carried out to evaluate the performance of the proposed method. Experimental results show that the proposed method is more stable and superior to the existing methods.

1. Introduction

Due to deregulation of power industry, aging infrastructure and many other factors, modern society is exposed to the risk of large-area blackouts. In recent years, several large-area blackouts occurred all over the world [20,30], such as the blackout in USA and Canada on August 14, 2003, the blackout in Italy on September 28, 2003, the blackout in Brazil on November 10, 2009, and the blackout in India on July 30, 2012. When a large-area blackout occurs, fast and reliable power system restoration is necessary since the blackout can have a catastrophic impact on the economy and society [2,24]. One of the most important techniques for restoring power systems is black-start. Black-start is defined as the process that a power system suffered from a complete blackout is restarted through reconfiguring its networks and recovering its loads depending on self-starting units (black-start units), without relying on other systems [12]. In a typical black-start scenario, black-start units provide power to non-black-start units located close to them, critical system loads are recovered when these non-black-start units come online, and the re-supplied area is gradually expanded until the entire power system is restored [4,29]. Optimizing black-start schemes is one of the key issues having impacts on the restoration speed of the power system concerned [26]. Up to now, many studies have been carried out on evaluating black-start schemes and restoring power systems.

Liu and Gu [12] presented a skeleton-network reconfiguration method, in which the importance of sources and loads are ranked, and discrete particle swarm optimization is employed to implement the reconfiguration. Qu and Liu [20] proposed a mathematical model to determine the maximum restorable load amount of a substation. Their model considers frequency constraint, transient voltage-dip constraint and steady-state voltage constraint, which is suitable for different restoration situations. Sun et al. [24] extended the implementation of multiple attribute decision making from the stage of black-start to backbone-network reconfiguration, and used an extended VIKOR method to evaluate backbone-network reconfiguration schemes. Park et al. [18] developed an expert system to evaluate restoration paths. This system first generates some feasible paths, and then suggests the optimal path by analyzing the reactive capability of black-start generators. Wang et al. [26] presented a black-start decision making method based on interval values, which focused on optimizing black-start schemes with uncertain information. Quirós-Tortós et al. [21] proposed a spectral clustering-based method to determine sectionalizing strategies for parallel power system restoration. Liu et al. [13] also focused on parallel power system restoration. They proposed a sectionalizing model for picking up critical loads, and used bi-level programming method to solve the proposed model. Taher and Sadeghkhani [25] described a neural network method to estimate

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temporary overvoltages during power system restoration. Liu et al. [14] focused on group decision-making environment, they proposed an intuitionistic fuzzy distance-based method to analyze the consistency of black-start experts' preferences. Sun et al. [23] proposed a Generic Restoration Milestones-based algorithm to assess the optimal installation location and amount of black-start capability. In the algorithm, the benefit from additional black-start capability is quantified in terms of system restoration time. Lin et al. [11] presented an entropy weight-based decision-making method to evaluate and optimize black-start schemes, in which the weight of an index is the combination of subjective and objective weights. Golshani et al. [5] developed an offline restoration planning tool for harnessing wind energy to enhance the resilience of power systems. The Wind-for-Restoration problem is formulated as a stochastic mixed-integer linear programming problem with generated wind energy scenarios. The problem is decomposed into two stages and solved with the integer L-shaped algorithm. Pesoti et al. [19] described an energy based technique called Robustness Area technique that measures the robustness level of power systems, as a helper for planning power system restoration. Jiang et al. [8] presented a model for decision support in power system restoration planning. In their model, a path search algorithm is integrated to find the optimal path through which the cranking power from black-start units to non-black-start units is delivered.

The weights of indexes play a very significant role in the process of black-start decision making. One of the most popular methods for calculating index weights is the entropy method. However, even for the same decision matrix, the results obtained by the entropy method are remarkably different when using different normalization methods. The entropy method is not stable which makes the final evaluation results of black-start schemes not completely reliable. To address this issue, in this article, we propose a novel black-start decision making method based on collaborative filtering (CF-BSDM). Our method first uses linear normalization or vector normalization methods to normalize the original decision matrix. Then, collaborative filtering is adopted to predict the withheld values in the decision matrix, and the average deviations for the indexes are calculated. Finally, the index weights are determined based on the resultant deviations, and the overall assessment value of each black-start scheme is computed according to the simple additive weighting method. The main contributions of this article are as follows:

(1) Collaborative filtering is used to determine the weights of indexes, which can more accurately express the relationships between indexes. To the best of our knowledge, this is the first work to adopt collaborative filtering to deal with the black-start decision making problem.
(2) Based on the data of Guangdong power system of China, experiments were carried out to investigate the effectiveness of the proposed method CF-BSDM, and to compare CF-BSDM with some popular methods. Experimental results show that CF-BSDM performs better than the existing ones.

The remainder of this article is organized as follows. In Section 2, we briefly review the previous studies related to our work. Section 3 describes the details of the proposed method. In Section 4, we present the performance of our method through experimental evaluations. Finally, the conclusions are given in Section 5.

2. Related work

2.1. Problem statement

We use a simple example to explain the normalization problem. Matrix A is a black-start decision matrix of Tianjin power system of China [10]. There are 5 black-start schemes and 5 indexes in the matrix A.

$$A = \begin{bmatrix} 29.9 & 21 & 50 & 15.47 & 2 \\ 30.18 & 18 & 200 & 15.06 & 1 \\ 30.18 & 21 & 200 & 15.07 & 1 \\ 56.65 & 33 & 135 & 5.01 & 4 \\ 60 & 23 & 330 & 6.53 & 3 \end{bmatrix}$$

Linear normalization and vector normalization methods [17] are adopted, respectively, to normalize the original decision matrix A. And normalized decision matrixs $B1$ and $B2$ are obtained:

$$B1 = \begin{bmatrix} 1.000 & 0.800 & 0.000 & 1.000 & 0.667 \\ 0.991 & 1.000 & 0.536 & 0.961 & 1.000 \\ 0.991 & 0.800 & 0.536 & 0.962 & 1.000 \\ 0.111 & 0.000 & 0.304 & 0.000 & 0.000 \\ 0.000 & 0.667 & 1.000 & 0.145 & 0.333 \end{bmatrix} \quad B2 = \begin{bmatrix} 0.535 & 0.466 & 0.109 & 0.561 & 0.321 \\ 0.530 & 0.544 & 0.437 & 0.546 & 0.642 \\ 0.530 & 0.466 & 0.437 & 0.546 & 0.642 \\ 0.283 & 0.297 & 0.295 & 0.182 & 0.161 \\ 0.267 & 0.426 & 0.721 & 0.237 & 0.214 \end{bmatrix}$$

Based on $B1$ or $B2$, entropy method [28,27] is used to calculate the weights of the indexes, and simple additive weighting method [27] is used to calculate the overall assessment value of each black-start scheme. Table 1 shows the index weights determined by linear normalization based and vector normalization based methods, and Table 2 shows the overall assessment values of black-start schemes. We observe that the weights obtained by the linear normalization based method are different from those obtained by the vector normalization based method, and the overall assessment values obtained by the two methods are also different. For the linear normalization based method, the 5 black-start schemes are ranked as $s_2 > s_3 > s_1 > s_5 > s_4$. But for the vector normalization based method, the schemes are ranked as $s_2 > s_3 > s_5 > s_1 > s_4$. According to the above analysis, we can see that even for the same decision matrix, the results obtained by different normalization methods are different. The normalization biases affect the final black-start decision making results.

2.2. Entropy method

The entropy method [28,27] is the most widely used method to determine the weights of attributes in multiple attribute decision making (MADM). Suppose there are m decision alternatives to be evaluated in terms of n attributes, which forms a decision matrix denoted by $A = [a_{ij}]_{m\times n}$, where a_{ij} is the performance value of the ith alternative with respect to the jth attribute. Due to the incommensurability among different attributes, the decision matrix $A = [a_{ij}]_{m\times n}$ needs to be normalized to eliminate its dimensional units. Let $B = [b_{ij}]_{m\times n}$ denote the normalized decision matrix, then the entropy of each attribute is computed as

$$E_j = -g\sum_{i=1}^{m} c_{ij}\ln c_{ij}, \quad j = 1,2,\ldots,n \tag{1}$$

where $g = 1/\ln m$, $c_{ij} = b_{ij}/\sum_{i=1}^{m} b_{ij}$, $0 \le E_j \le 1$, and for $c_{ij} = 0$, $c_{ij}\ln c_{ij}$ is always set as zero because $\lim_{c_{ij}\to 0} c_{ij}\ln c_{ij} = 0$.

The entropy weight of each attribute can be determined through the following formulation:

$$w_j = \frac{1-E_j}{n-\sum_{j=1}^{n} E_j} \tag{2}$$

where $0 \le w_j \le 1$, and $\sum_{j=1}^{n} w_j = 1$.

Table 1
Weights of the 5 indexes by different normalization methods.

	y_1	y_2	y_3	y_4	y_5
Linear normalization based method	0.246	0.145	0.193	0.231	0.185
Vector normalization based method	0.106	0.042	0.315	0.212	0.325