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Second-order conic programming model for load restoration considering uncertainty of load increment based on information gap decision theory

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ABSTRACT

Load restoration is an important issue for power system restoration after a blackout. A second order conic programming (SOCP) model is proposed based on the information gap decision theory (IGDT) to maximize load pickup considering the uncertainty of load increment. Because distribution functions of load increment are difficult to obtain, the optimization of load pickup is transformed to maximize the fluctuation range of load increment by the IGDT. The derived optimal fluctuation range can ensure that the reenergized system is secure, and the amount of load pickup is always better than the specified expectation. Moreover, because the optimization model of the fluctuation range is a mixed-integer nonlinear model which is challenging to solve accurately and efficiently, the nonlinear model is transformed into a SOCP model that can be efficiently solved using CPLEX. The efficiency of the IGDT-based SOCP model is validated using the New England (10-machine 39-bus) system. The simulation results show that the derived load pickup shows expected robustness with respect to the load increment uncertainty.

1. Introduction

Load restoration is an important issue for power system restoration after a blackout. Large-area blackouts of a power system have occurred many times in the past decade, e.g., the Indian blackout in 2012 [1] and the Japanese blackout in 2010 [2], because power systems are operating close to their limits as a result of the deregulation of the power system [3]. In order to restore the systems quickly and safely, the restoration procedure of a power system is commonly divided into three stages: preparation, system restoration and load restoration [4]. In the system restoration stage and load restoration stage, load pickup can balance the output of generators and provide frequency and a voltage profile for the restored system. Load pickup can be optimized to maximize restored loads with the operational constraints of the power system and generators to reduce the blackout duration time of loads [5,6].

A lot of research has been conducted to optimize the load pickup. Because the load is picked up discretely, load restoration may result in frequency deviations, transient voltage sags, and power flows over the limit. The load behaviour characteristics of various types of industry loads were modeled in [7,8]. An assessment method of the frequency response of cold load pickup in the restoration was proposed in [9]. The optimization model of load pickup for a specific substation was established in [5], considering the security constraints of dynamic frequency and voltage, steady-state power flow and cold load pickup. A battery storage system was employed in [10] to maximize the load pickup by maintaining frequency stability. The load restoration was optimized using a multi-agent consensus system in [11]. The penalty costs were considered in [12] to decrease the load restoration time. A two-stage hierarchical optimal model of load restoration was built in [13] based on synchrophasor technology. The induction of the decision tree was employed to select the load pickup sequence in [14].

In the above research, the actual load pickup in each step of the load restoration is assumed to be the same as the forecasted load pickup. However, when the distribution feeders with loads are restored, some devices may not restart, e.g., some motors will not work immediately after the restoration of power supply; some devices may consume more power than normal operation, e.g., the air conditioner may consume more power than normal operation. Consequently, the actual load increment fluctuates around the forecasted load increment. A large difference between the actual and forecasted load increment may result in a security problem in the restored systems and decrease the efficiency

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of system restoration. For example, during the system restoration following the "8-14" blackout in the USA and Canada in 2003, an emergency demand response plan was implemented by the New York Independent System Operator (ISO), and 300 MW of load was shed because the actual load pickup was larger than the forecasted load pickup [15]. Benefitting from the successful implementation of the emergency control, the system restoration was only delayed by the accident. If the emergency control is not implemented properly, then the restored system may fail again. Consequently, it is necessary to optimize the load pickup considering the uncertainty of the load pickup.

The challenge of considering the uncertainty of load pickup is the modeling of uncertainty. Because of the challenges of modeling, the wide area monitoring system (WAMS), which can monitor the system parameters and provide more accurate measurements of the restored load, was employed to reduce the time step of load restoration and decrease the uncertainty of load pickup in [6]; however, the forecasted load increment was different from the actual load increment. The fuzzy chance constraint model was used to describe the uncertainty of load pickup in [16]; however, the accurate fuzzy parameters were challenging to obtain in the application of this method. Apart from fuzzy arithmetic, various methods exist for handling uncertainty, such as the probabilistic method and robust method, which are frequently used in power system dispatching [17]. Due to the lack of historical data, the probability density function is challenging to obtain, whereas the Information gap decision theory (IGDT) requires less prior knowledge of the uncertainties, making it more suitable for optimizing load pickup, which has been applied to power system operation with uncertain parameters [18,19]. In [20], the IGDT was employed to restore distribution networks considering the uncertainty of load. However, because the system characteristics, restoration requirements, restoration model for load restoration during transmission system restoration are different from distribution network restoration, the method in [20] cannot be directly applied to the load restoration in this paper.

The contribution of this paper is proposing an IGDT-based second-order conic programming (SOCP) model to optimize the load restoration considering uncertainty of load increment. Specifically, according to the IGDT, the optimization of load pickup is transformed to maximize the fluctuation range of the load increment in which the reenergized system can remain secure and the amount of load pickup is always better than a specified expectation. Furthermore, the nonlinear model of fluctuation range optimization is transformed into an SOCP model that can be efficiently solved using CPLEX. Compared to the fuzzy method and probabilistic method, the IGDT-based SOCP model requires little information of the probability distribution function of the load increment fluctuation and can efficiently determine the load pickup scheme.

The rest of the paper is organized as follows. Section 2 describes the robust optimization model of load restoration by IGDT. Section 3 presents details on the construction and solution of the SOCP model. The simulation results are presented in Section 4, followed by the conclusion.

2. Problem formulation

To address the uncertainty of load increment for load restoration, an IGDT-based load restoration model is established to optimize the load pickup in this section.

2.1. Overview of IGDT model

A typical optimization model can be described as follows:

$$\begin{cases} \max\limits_{d} B(X, d) \\ s.\,t. \quad H(X, d) = 0 \\ \qquad\;\; G(X, d) \leqslant 0 \end{cases} \tag{1}$$

where X refers to the vector of input parameters representing the load increment in different load nodes in this study, d refers to the vector of decision variables representing the restoration states of different load nodes, $B(X, d)$ refers to the optimization objective that maximize the load pickup, and $H(X, d) = 0$ and $G(X, d) \le 0$ are the equality and inequality constraints, respectively.

When the input parameter X is an uncertain load increment, this parameter can be modeled in several forms using the IGDT [21]. The envelope bound model is employed in this study. Assuming that $\widetilde{X}$ is the forecasted amount of uncertain load increment X and α is the uncertain range of X, the model of X can be expressed as,

$$\begin{cases} X \in U(\alpha, \widetilde{X}) \\ U(\alpha, \widetilde{X}) = \{X: |(X - \widetilde{X}) \leqslant \alpha\} \end{cases} \tag{2}$$

where $\mathrm{U}(\alpha, \widetilde{X})$ is the set of all values of X whose deviation range from $\widetilde{X}$ is less than α.

When the value of uncertain load increment is equal to the forecasted value, the objective value B_0 will be the maximum load pickup. However, the value of load increment typically fluctuates around the forecasted value. In order to make the obtained optimal result robust against the possible errors of the forecasted load increment, the load pickup should be optimally determined so that the actual objective function is robust against the deviation of load increment from its predicted value. It is obvious that a robust decision is reached when the objective function is robust against the maximum fluctuation range of the uncertain load increment. Therefore, the robust optimization model is formulated as,

$$\begin{cases} \max \alpha \\ s.\,t. \quad \min B(X, d) \geqslant B_{\mathrm{m}} \\ \qquad B_{\mathrm{m}} = (1 - \delta) B_0 \\ \qquad H(X, d) = 0 \\ \qquad G(X, d) \leqslant 0 \\ \qquad X \in U(\alpha, \widetilde{X}) \end{cases} \tag{3}$$

where B_{m} is the pre-specified minimum load increment that the new $B(X, d)$ should not surpass; B_0 is the optimization result of the deterministic model in (1). This value of B_{m} can be pre-specified based on the requirements of the decision maker as an input parameter. This value is generally defined as a linear function of B_0 with the coefficient δ that indicates the degree of robustness against the value B_0. The range of coefficient δ is within the interval $[0, 1)$. If the decision maker is risk-averse, a smaller value of B_{m} can be selected to ensure that α is larger than the actual deviation range. If the decision maker is risk-neutral, a larger value of B_{m} can be selected to restore more loads with the risk that α may be less than the actual deviation range.

The solution of the above optimization model can obtain a maximum fluctuation range of the uncertain load increment and a load pickup scheme that ensures the amount of load pickup is bigger than the pre-specified minimum load increment. In other words, the solution is robust against unfavorable fluctuation of the uncertain parameter from the forecasted value and satisfies the minimal requirements for system operation.

2.2. Deterministic load restoration optimization model

In real-time restoration, the coordination of restoration participants is complicated. The execution of the restoration actions heavily relies on the communication and collaboration among various participants. This paper mainly focuses on the restoration scheme, and assumes that the communication and collaboration among various participants is