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Hybrid probabilistic-possibilistic approach for capacity credit evaluation of demand response considering both exogenous and endogenous uncertainties

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HIGHLIGHTS

- Capacity credit (CC) of demand response (DR) under the smart-grid is assessed.
- Proposed a hybrid probabilistic-possibilistic framework for DR modeling.
- Both exogenous and endogenous uncertainties associated with DR are considered.
- A reliability-based algorithm combining operation optimization is developed.
- The impacts of various factors on DR CC are analyzed through numerical studies.

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ABSTRACT

As a featured smart-grid technology, demand response (DR) provides utility companies with unprecedented flexibility to improve the reliability of electricity service in future power systems. However, due to the uncertainties arising from the demand side, the extent to which DR can be utilized for capacity support poses a major question to the utilities. To address this issue, this paper proposes a new methodological framework to assess the potential reliability value of DR in smart grids. The framework is established on the concept of capacity credit (CC), and it accommodates different types of uncertainties (i.e., probabilistic and possibilistic) accrued from physical and anthropogenic factors in DR programs. The capability of DR during operation is considered as a synthesized result of multiple facets, i.e., users' load characteristics, participation levels, and load recoveries, and different models are developed to represent each component. To characterize the stochastic nature of demand responsiveness, the fuzzy theory is introduced, and possibilistic models are proposed to describe the human-related uncertainties under incomplete information. In addition, considering that in reality, DR operation could affect the comfort of customers, the dynamics of demand-side participation have also been incorporated in our study, in which two utility-based indices are defined to quantify the effect of such interdependency. Using a probabilistic propagation technique, the different types of uncertainties involved can be normalized and systematically addressed under the same framework. Then, the relevant models can be applied to the CC evaluation procedures, wherein two dispatching schemes (i.e., reliability-driven and coordinated management) are considered to study the effect of DR operation on its CC. The proposed methodology is tested on a modified RTS system, and the obtained results confirm its effectiveness.

Abbreviations: ARMA, autoregressive moving average; CC, capacity credit; CF, correlation factor; CGU, conventional generation unit; CM, coordinated management; DF, disturbance factor; DR, demand response; ECC, equivalent conventional capacity; EENS, expected energy-not-supplied; EFC, equivalent firm capacity; EGCS, equivalent generation capacity substitution; ELCC, effective load-carrying capability; ENS, energy-not-supplied; FOR, forced outage rate; LF, load flexibility; LR, load recovery; MTTF, mean time to failure; MTTR, mean time to repair; NRL, non-responsive load; OPF, optimal power flow; PD, possibilistic distributions; PDF, probabilistic density function; PL, participation level; RD, reliability-driven; REG, renewable energy generation; RF, response frequency; RI, response intensity; RL, responsive load; SG, smart-grid; SMCS, Sequential Monte Carlo simulation; UC, utility company; WT, wind turbine

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1. Introduction

As an advanced smart-grid technology, demand response (DR) provides utility companies (UCs) with an efficient means to manage power system operation by exploiting the demand-side flexibilities via economic or financial mechanisms [1]. Unlike traditional supply-side resources, the implementation of DR does not rely heavily on physical devices; thus, its extensive deployment is expected to yield significant benefits to different stakeholders in the electricity market.

For customers, participating in DR programs not only can help reduce their electricity bill but also may yield additional rewards [2]. For the regulator, DR can temper price spikes and mitigate the risk of market power abuses [3]. In addition, as DR reshapes the load profile of customers, the grid operator can also use DR as a tool to address network congestion [4] and to enhance the utilization of renewable energy sources [5,6], such as wind or solar, in future smart-grid (SG) systems.

Although the potential benefits of DR have been proven notable, one of its most relevant aspects for UCs lies in its contribution to the reliability of supply. In a competitive market, regulators normally impose mandatory limits on the frequency and duration of customer interruptions; thus, UCs are under great pressure to maintain and improve the reliability of their services, as failing to deliver the required targets can lead to severe penalties [7]. However, as a remedial scheme, DR can reduce the load demand and provide capacity supports to the grid in times of emergency. This would help enhance the load-carrying capability of the system and thus enable UCs to meet reliability commitments without incurring additional capacity expansion [8].

In recognition of the significant role that DR could play, a number of pioneering studies have been conducted on this issue in recent times. By using the sequential Monte Carlo simulation (SMCS) technique, the impact of DR on the adequacy of distribution systems is examined in [9]. In [10], Syrri et al. present a comprehensive techno-economic assessment approach to quantify the capability of post-fault DR to provide release for generation capacity. An optimal power flow (OPF) approach was used for the selective disconnection of DR customers according to a priority list, which reflects the reliability value of power interruptions. In practice, as a decrease in energy usage could be detrimental to users' wellbeing, to compensate for such losses, customers tend to restore their load demand after DR events. This load recovery (LR) effect was also examined in [11]. Additionally, a systematic evaluation framework for the capacity credit (CC) of DR was proposed in [12]. Ref. [13] also presents a sequential state-enumeration-based method that is suitable for system reliability evaluation with DR. For most DR analysis, the reaction of responsive loads to imposed schemes is typically represented using a linear model. However, in reality, due to potential economic and social reasons, the behaviors of responsive users might differ and may not follow a linear pattern consistently during operation. To address this issue, *Rahmani-andebili* presents a novel nonlinear model for DR programs and implements the method on several real power markets [14]. Based on the work of [14], the author further introduces the model into the unit commitment study [15] and concludes that impractical modeling of the DR behavior may result in significant errors in the final decision. In addition, a new representation for DR programs that includes the effects of both incentive and penalty on the load demand is also developed in [16]. By using the proposed model, the system operator may evaluate the behaviors of customers more precisely and therefore identify the best DR strategy under different market settings.

In all the above literature [9–16], the demand responsivity of customers (i.e., responsive load behavior) is assumed to be a constant, which can be known or perfectly forecasted by the UC in advance. However, in real-world situations, as users may have different consumption patterns and preferences, it is not easy for UCs to learn the idiosyncrasies of each DR customer. Moreover, even if such information is attainable, the responsivity of individuals can also be affected by various other factors, e.g., special events, the effects of which are difficult to quantify through a deterministic model. For this reason, the actual DR capacity of the system should be highly uncertain to the UCs during operation. However, such uncertainty issues regarding DR were barely considered in the works of [9–16].

To fill this gap, a new algorithm for the short-term reliability evaluation of DR-integrated power systems was proposed in [17], explicitly accounting for the impacts of DR variability. The uncertainties of DR have also been discussed in [18]. In this research, the responsiveness of consumers to the electricity prices was modeled by a stochastic price-elastic demand curve, which can vary within a certain range to capture the potential effects of DR failures on the system. Additionally, the authors of [2] proposed a real-time price-based DR management for residential appliances, wherein the dynamics in electricity prices were considered and represented by using a Gaussian distribution. The parameters for the model are determined according to the real price data collected from the market. Furthermore, a long-term probabilistic framework for analyzing the reliability contribution of DR was also presented in [19], and multiple interactions among the generators and price-responsive demand were considered. In addition, similar studies with respect to different types of DR programs considering uncertainties can be found in [20], [21] and [22].

For all the studies presented above [17–22], the uncertainties of DR were mostly modeled as a fixed probability distribution that can be fully determined before the assessment. In other words, existing researches regard the demand responsivity of users as an *exogenous* uncertain variable, which is independent of the control strategy adopted by the operator. [In economics, *exogenous* uncertainties are generally referred to as the inputs whose variation can be determined outside the system boundary and are independent of the external control, as they arise from the marketplace itself. In practice, if an uncertain variable follows a specific statistical regularity, which might be known in advance, and does not change with time, we can refer to this case as exogenous uncertainty; otherwise, we will talk about *endogenous* uncertainty.] However, in actual conditions, the participation of DR can provide customers with financial rewards but may also decrease their wellbeing (comfort) [23]. Improper scheduling tactics would potentially lead to fatigue of users and reduction of their compliance level to DR calls[1] [24]. As such, the actual distribution of the users' responsivity not only depends on its future outcomes but also is affected by the operation decisions of the grid. Thus, failing to incorporate such a dependent and dynamic nature of DR is likely to cause a misestimation for its reliability benefits. However, the existing works [17–22] did not fully consider this issue (*endogenous* uncertainties of DR).

To fill this gap, in this study, a novel probabilistic-possibilistic framework for the CC estimation of DR from the perspective of UCs is proposed. Unlike the existing works, the stochastic feature of DR and its correlation with the operation decisions is explicitly considered in our analysis. For this purpose, we first divide the influential factors of DR into several aspects, and different models are proposed to represent each component. To quantify the disutility of users due to DR, two evaluation indices (frequency-based and intensity-based) are defined; these indices are formulated as a function of DR operation decisions. Additionally, considering the ambiguity of individual idiosyncrasies, a fuzzy approach is employed to model the DR uncertainties under incomplete information. Using a probabilistic propagation technique, the different types of (probabilistic and possibilistic) uncertainties concerned in the study can be normalized under the same framework. To demonstrate the practicality of the proposed model, we exemplify its usage in DR's CC estimation, which is implemented from the perspective of the UC.

The structure of this paper is organized as follows. Section 2 introduces the metrics used for quantifying the DR CC. Section 3 describes

[1] This can be especially true in DR programs if no penalties are imposed for the violation of DR calls.