Electrical Power and Energy Systems 94 (2018) 311–320

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

How to build an electric power transmission network considering demand side management and a risk constraint?

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ARTICLE INFO

Article history:
Received 1 February 2017
Received in revised form 1 July 2017
Accepted 27 July 2017

Keywords:
Network planning
Decomposition
Incentive-based demand response
Risk constraint

ABSTRACT

The increasing penetration of intermittent renewable energy poses plenty of challenges to electricity networks. Moreover, following the applications of intelligent electricity networks, demand response (DR) has attracted a great deal of attention due to its positive effects on shaving peak demands and balancing power supply and demand. On the other hand, when DR reaches a critical market level, the market behavior of DR becomes a meaningful uncertainty to the networks as well. Therefore, power transmission expansion planning (TEP) becomes a complicated decision-making process requiring risk analysis. This paper proposes a probabilistic approach to TEP contemplating risk. The conventional reliability criterion is replaced by a risk constraint. In addition, the TEP problem is decomposed into a master investment problem and two slave subproblems, i.e., optimal operation and feasibility check subproblems. The proposed TEP model is tested on the Garver's six-bus and the modified IEEE 24-bus RTS and Polish 2383-bus systems. According to the numerical results, the proposed TEP model is superior compared to the conventional reliability-driven TEP from three perspectives: (1) It has incorporated a risk constraint and hence can help network planners understand the variants of risk and provide the opportunity to make trade-offs between cost, reliability and risk. (2) It still enforces the reliability criterion and is more cost-effective when the wind power uncertainty becomes higher in the future. (3) It allows risk-analysis, giving decision-makers the flexibility to choose a plan according to their individual risk-aversion levels and understand the multiple outcomes.

1. Introduction

Wind power has increased significantly over the past decades due to the concern on climate change. However, wind power is heavily dependent on meteorological conditions (i.e., wind speed variations), and its outputs cause unpredictable power flow fluctuations on transmission lines [1]. Moreover, wind resources are often high in remote locations, while networks tend to be well meshed in heavily populated areas [2]. A one well-known fact is that there is lack of transmission capacity to integrate the large-scale distant wind farms into power systems [3]. This means that in some cases wind energy might have to be curtailed. How to reinforce and expand a power network to absorb the intermittent wind power and satisfy the growing energy demand is therefore of significance. Power transmission expansion planning (TEP) refers to when, where and how many lines should be built in order to meet the growing energy demand [4,5]. Conventionally, TEP is formulated as a cost minimization problem, subject to the reliability criterion that encompasses security and adequacy [6]. Moreover, the power industry deregulation and the increasing penetration of intermittent renewable energy have brought in many uncertainties to TEP [7]. Meanwhile, demand response (DR) has attracted significant attention over the past few years in terms of how to improve the controllability and flexibility of the network, such as using DR to shave peak demand or balance renewable energy fluctuation. When DR reaches a critical market level, the inaccuracy of DR would inevitably pose challenges to TEP as well [8].

DR is defined as adjustment in electricity consumption by end-use customers (including load increase and decrease), in response to changes in market prices, incentive payments or network reliability signals [9]. Generally speaking, DR can be classified into two types: price-based DR (PBDR) and incentive-based DR (IBDR) [10]. With regard to PBDR, customers can actively change their demand in response to price signals (e.g. time-of-use tariff). With regard to IBDR, system operators have the contractual authority to curtail customer power load directly when necessary. Or customers receive financial compensations if they reduce electricity consumption voluntarily when requested. Since DR may have meaningful impacts on TEP, DR resources and their economic values should be carefully addressed. Please be noted that in this paper

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http://dx.doi.org/10.1016/j.ijepes.2017.07.019
0142-0615/

DR only refers to incentive-based DR only (interruptible load) (IBDR). In addition, we do not assume that a utility is allowed to totally curtail the demand of a node. The load aggregators are assumed to represent energy end users to participate in market operations with the independent system operator (ISO). In other words, load aggregators integrate the portfolio of interruptible loads at nodes and act as a representative that manages interruptible electric appliances (e.g. hot water systems, swimming pool pumps) of end users. This load integration can make the summed capacity of many small-scale interruptible loads be large enough to trade energy or provide network support services in pool markets. The load aggregator signs a contract with interruptible consumers, in which the upper limit, cost, and permitted hours of load curtailment are specified. The advanced communications networks in smart grids are the foundation for the bi-directional communication, monitoring, and control.

TEP is a complicated decision-making process. Network planners need to understand the multiple choices they have and the multiple outcomes related to uncertainties in future (e.g. load growth, bidding strategies of power generation companies or DR, closure or installation of power generation units) [11]. In terms of how to handle uncertainties, TEP can be classified into three types [12]: (1) deterministic approach, where the worst-case is modelled; (2) probabilistic approach, where a plan is expected to be optimal in the statistical sense (i.e., calculating the mean value); (3) risk-based approach, where comprehensive risk analysis is conducted. Risk analysis means studying the different scenarios and their optimal solutions, in order to obtain the most robust solution based on individual needs [13].

Generally speaking, TEP can be solved by mathematical approaches or heuristic based approaches. Mathematical programming methods have strict requirements on the model itself. For example, the problem or the continuous relaxation of the problem should be convex. The mathematical programming methods can provide more clues on the quality of the final solution, but they might be trapped by local optima in some cases [14]. On the contrary, heuristic programming methods are free from problem formulation difficulties and can escape from premature local optima (i.e., stochastic global search). The drawback of heuristic methods is that the quality of the solution cannot be guaranteed and intensive computation efforts are required [14,15].

In the literature, many efforts are made to address uncertainties or risks involved in TEP. For instance, in [16], a Benders decomposition approach is proposed to solve TEP, and load and wind curtailment costs are modelled. Ref. [17] proposes a methodology for planning the optimal reliability indices of system components. The non-sequential Monte Carlo (MC) simulation method is used and the model is solved by the particle swarm optimization (PSO) algorithm. Ref. [18] proposes a criticality index in transmission system planning, and then a deterministic TEP model is proposed in deregulated electricity markets. Ref. [19] proposes a novel heuristic reliability algorithm, and Benders decomposition has been employed to solve the formulated mixed-integer nonlinear programming problem (MINLP). Ref. [20] applies the risk of not meeting load by chance constraints into the AC power flow equations as a set of convex equations. Ref. [21] proposes a planning model in association with air pollution control and uncertainty analysis. Ref. [22] proposes a least cost generation planning model with wind power plant and emission. The differential evolution algorithm is employed to solve the formulated nonlinear model. Ref. [23] proposes an innovative robust method for addressing uncertainties in electric power system planning. Ref. [24] presents a market-based TEP model, which can compute the probability density function of nodal prices. The model is mean value based and selects a final plan after risk assessment. In [25], a multi-year TEP planning model is proposed, and congestion metrics is used to measure changes in nodal prices and line congestions. Ref. [26] proposes a reliability assessment method for renewable distributed generation such as wind power. Ref. [27] presents a stochastic coordination of generation and transmission expansion planning. The Monte Carlo (MC) simulation method is applied to consider uncertainties of outages of generating units and transmission lines as well as long-term load forecasting. The expected value of objectives is obtained after MC simulations converge. Ref. [12] presents a generation and transmission expansion model, in which a risk factor based on the mean-variance Markowitz theory is incorporated. The expected value of perfect information is obtained. Ref. [28] presents a coordinated planning model for wind power integration while considering static voltage stability constraints. Ref. [29] proposes a chance constrained TEP model to tackle the uncertainties of load and wind power, and is computationally efficient. Ref. [30] considers an upper bound on total load shedding, which helps to identify planning schemes that have an acceptable probability of load curtailment. Ref. [31] proposes a chance-constrained TEP. Ref. [32] proposes a risk-based approach to TEP under deliberate outages. The network vulnerability against intentional attacks is addressed subject to budgetary limits. Ref. [33] has incorporated the risk of blackouts into the cost minimization in probabilistic TEP. The problem is solved by a multi-objective particle swarm optimization method. Ref. [34] presents a risk/investment driven TEP model with multiple scenarios. Their models can provide network planners with a meaningful risk analysis, which enables them to determine the required investment at a permissible risk level. Unfortunately, the above-mentioned models have not taken into account the optimality of DR resources, which are emerging applications in smart grids. Moreover, Ref. [10] presents a probabilistic TEP model considering large-scale wind farms integration and incentive-based DR. The wind speed correlation between wind farms is modelled by a multi-state wind farm model. Ref. [35] proposes a comprehensive generation and transmission planning model while considering DR as an option for reducing operation costs. However, these references have not taken into account the upward DR (load increment). As a result, in their models, the DR's role in balancing wind power fluctuations (e.g. underestimated wind power outputs) is neglected.

In this paper we have proposed a probabilistic TEP model incorporating a risk constraint and DR. We extend the work of [30], formulate a risk constraint which can help to obtain optimal planning schemes that have an acceptable probability of load curtailment bounded by a threshold. Rather than only providing a binary answer to the system reliability (i.e., either acceptable or unacceptable reliability), this constraint gives a quantitative measure of system reliability and distinguish between conditions that are both considered as reliable but with different reliability levels. More importantly, the risk constraint can capture the probabilistic nature of system behaviors. It can provide network planners with an opportunity to conduct risk analysis. Low-probability but high-loss scenarios can be explicitly addressed when adjusting risk-aversion levels. Also, we develop a stochastic planning framework incorporating the risk constraint and economic values and market uncertainties of DR, including upward and downward DR. This framework is a useful decision-making support tool, helping network planners comprehend the variants of risk. Thus they can make trade-offs between cost, reliability and risk according to their individual needs. Besides, the original mixed integer nonlinear programming problem is decomposed into a master problem and two slave subproblems, and they are solved iteratively until no violation exists. The master problem is an integer programming problem that identifies the optimal expansion plans. The optimal operations subproblem is to minimize the total operating cost and the feasibility check subproblem is to minimize the probability of load curtailment above the threshold. As a result, our model can