CONGESTION MANAGEMENT IN ACTIVE DISTRIBUTION GRIDS: OPTIMAL RESERVE SCHEDULING UNDER DISTRIBUTED GENERATION UNCERTAINTY

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ABSTRACT

An important component in the modernization of electrical grid infrastructure is the increasing production of energy from renewable distributed generation sources. However, the intermittency of this generation motivates stochastic optimization to address uncertainty, and an adequate system of reserves. This paper investigates the stochastic optimization of a two-tiered distribution reserve system for congestion management.

INTRODUCTION

The utilization of renewable energy technologies for expansion of the electrical energy infrastructure is a vital component of future energy scenarios. The societal benefits created through the use of carbon-free renewable energy technologies, when considered in parallel with long-term increases in the costs of fossil fuels and the low marginal energy production costs of renewable sources, ensures a continuous expansion of renewable energy integration. While the benefits of increasing renewable energy generation are readily identifiable, there are certain additional challenges inherent to these technologies which must be addressed to maintain secure and economically-efficient operation of the network.

The power generated by renewable energy sources is intrinsically uncontrollable, which implies that the power output of these sources cannot be dispatched when a modification of the generation schedule is necessary, nor can the power generated by these sources be predicted with complete certainty [1]. At low penetration levels, the small amount of implied uncertainty poses little threat to the stability of the system. However, with the expected proportional increase in generation coming from renewable sources, this uncertainty in generation must be adequately anticipated and planned for to avoid a failure in system security. Addressing the non-dispatchable and unpredictable nature of renewable generation requires a more sophisticated technique for congestion management. [2]

For such cases, it is important to consider not only the expected deterministic power generation forecast of the renewable sources, but also to take into account the potential stochastic variation in the power output [3-5]. The uncertainty in the generation of the renewable sources will inevitably require that a stochastic optimal power flow solution be applied to adequately prepare for such uncertainties through the provision of reserve[6]. In the case of a distribution system, these reserves will be provided through vehicle-to-grid services and any additional local electrical storage.

This paper investigates the optimal scheduling of a two-tiered distribution grid reserve system to alleviate any network stress caused by the unpredictable output of the renewables integrated within the distribution network [7]. Based on the probabilistic nature of the renewable generation, the scheduling algorithm will seek to determine the proper amount of pre-purchased reserve capacity, as well as the amount of additional balancing reserve which may need to be purchased in real-time. It will be shown that the proposed algorithm can be utilized to develop a schedule to maximize the expected economic benefit while preventing network congestion. Additionally, the algorithm may be used to analyze the increased costs of energy delivery given the level of uncertainty.

PROBLEM FORMULATION

The fundamental objective in obtaining an optimal solution for the scheduling of active distribution network resources is to determine the schedule which will minimize the cost of grid operation. The algorithm utilized to determine the optimal schedule will seek to minimize expenditures and maximize profits during grid operation, thus leading to the most cost effective solution. Within a practical distribution network, a number of physical limitations are present which constrain the optimal schedule, and which must be accounted for during optimization.

In order to address the needs of such an optimization, a nonlinear constrained optimization problem must be formed which accurately portrays the power demands, generation sources, active network resources, and binding network constraints. In its most general form, the equations which comprise the nonlinear constrained optimization problem can be written as

$$\begin{aligned} \min \quad & f_C(\mathbf{V}, \mathbf{\Theta}, \mathbf{u}) \\ \text{s.t.} \quad & \mathbf{g}(\mathbf{V}, \mathbf{\Theta}, \mathbf{u}) = 0 \\ & \mathbf{h}(\mathbf{V}, \mathbf{\Theta}, \mathbf{u}) \leq 0, \end{aligned}$$

where the function $f_C(\cdot)$ is the cost function which serves as the minimization objective of the algorithm, $\mathbf{g}(\cdot)$ is the set of equality constraints, and $\mathbf{h}(\cdot)$ is the set of inequality constraints applied during optimization. The variable vectors $\mathbf{V}$ and $\mathbf{\Theta}$ contain the node voltage magnitudes and phase-angles of the node voltages respectively, and the decision variable vector $\mathbf{u}$ contains all other decision variables, including but not limited to shiftable load scheduling, vehicle-to-grid scheduling, and load/generation curtailment.

While a large portion of the constraints utilized in the optimization are linear constraints, the set of constraints which govern the power flow equation and maximum apparent power through a line are inherently nonlinear, and necessitate the use of an optimization algorithm which can incorporate such constraints. The set of power flow constraints belong to the constraint set $\mathbf{g}(\cdot)$, and are defined as

$$\sum P_n(\mathbf{V},\mathbf{\Theta},\mathbf{u}) = 0,$$

where $\sum P_n$ is net power flow to node n, whereas the constraints applied to the maximum apparent power in a line belong to the set of inequality constraints $\mathbf{h}(\cdot)$, and are defined as

$$S_l(\mathbf{V},\mathbf{\Theta},\mathbf{u}) - S_{l,\max} \leq 0,$$

where S_l is the nonlinear function determining apparent power flow in line l, and $S_{l,max}$ is the maximum allowed apparent power in the given line. The inclusion of these nonlinear constraints is necessary for obtaining an optimum solution that adheres to the physical behavior of the distribution network, but nonlinear constraints place a significant computational burden on the optimization, and should be minimized if at all possible. A reduction in the quantity of nonlinear constraints can be achieved through a network aggregation procedure.

To properly account for the probable discrepancy between the predicted amount of renewable generation and the actual generation, it is important to include not only the predicted renewable generation schedule in the optimization, but also include stochastic elements within the optimization. First, the optimization should ensure that none of the system constraints are violated over the entire range of possible variations in generation, thus guaranteeing feasibility. Second, the stochastic properties of the renewable generation should be included into the optimization to determine the schedule which will maximize the expected profit.

Incorporating the stochastic uncertainty of renewable generation can be accomplished through an expansion to the formulation of the optimization problem, which will now include the parallel simulation of multiple generation scenarios with varying probabilities of occurrence. Thus, the optimization will now take the form

$$\begin{aligned} &\min \quad f_C(\mathbf{V},\mathbf{\Theta},\mathbf{u}) \\ &\text{s.t.} \quad \mathbf{g}_s(\mathbf{V},\mathbf{\Theta},\mathbf{u}) = 0, \quad s = 0,\dots,N_S \\ &\mathbf{h}_s(\mathbf{V},\mathbf{\Theta},\mathbf{u}) \leq 0, \quad s = 0,\dots,N_S \end{aligned}$$

where $\mathbf{g}_s$ and $\mathbf{h}_s$ are the sets of equality and inequality constraints respectively, expanded to include the set of N_S potential renewable generation scenarios. The subscript s indicates which of the scenarios the constraint is associated with, where $s = 0$ is the expected base case scenario, and $s = 1,\dots,N_S$ indicate scenarios with stochastic variation from the base case. Additionally, the cost function is modified to incorporate the stochastic uncertainty, reformulating it as the weighted sum of the individual scenario cost functions, and becomes

$$f_C(\mathbf{V},\mathbf{\Theta},\mathbf{x}) = \sum_{s=0}^{N_S} P_s \cdot f_{C,s}(\mathbf{V},\mathbf{\Theta},\mathbf{u})$$

where the weight values P_s are the probability of occurrence for a given scenario s, and $f_{C,s}(\cdot)$ is the cost function for the individual scenario. Utilizing an optimization structure of this form enables the inclusion of stochastic uncertainty in the optimization, but it is readily apparent that the number of constraints in the optimization increases by a factor of N_S at a minimum, since each scenario requires a duplicate of the original constraints. Additionally, there may be further constraints added to the optimization due to the parallel stochastic scenarios, where the new constraints govern the interactions between the various scenarios.

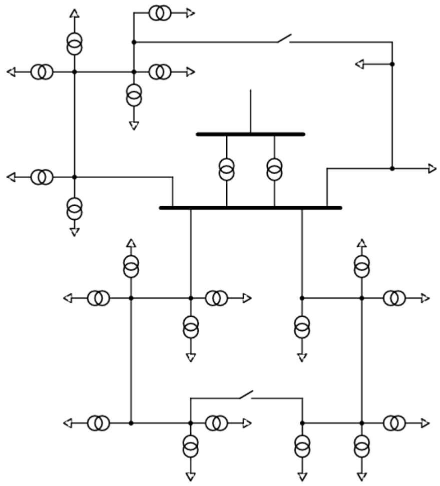

Figure 1: 58-node example distribution system utilized for testing of the proposed algorithm.

SIMULATION EXAMPLE

The proposed methodology is applied here to simulate an example 58-node distribution test network [9] shown in Fig. 1, in order to determine the optimal resource schedule. For the given test case, a preliminary aggregation procedure is applied to determine the set of possible binding constraints. In this example, only the two parallel substation transformers were found to be at risk of violating the maximum apparent power constraint, and so the distribution network is aggregated to form the reduced-order network on which the optimization will be performed.

Within the reduced network, the deterministic components remaining are the load demands and an aggregated loss component. The stochastic element within the aggregated network is a wind farm, and the active resource to be optimized is the acquisition and deployment of vehicle-to-grid reserves. For this test case, the vehicle-to-grid reserve is implemented as a two-tier system, where reserve capacity can be purchased in advance in preparation for a potential generation shortage, and additional balancing reserves can be purchased in real time to address any generation discrepancy, though the purchase of real time balancing reserves will come at an economic premium.

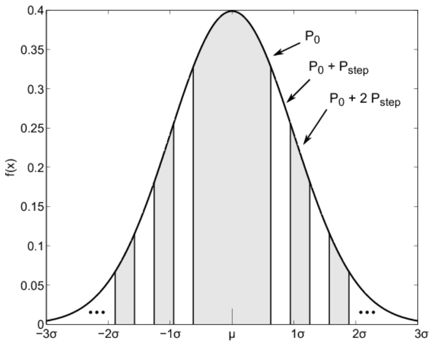

Figure 2: Segmented probability distribution chart displaying how the probability and variance of the scenarios are generated from a Gaussian distribution.

The stochastic uncertainty of the wind farm generation is incorporated into the optimization by first generating an hourly prediction of the expected generation schedule, and then defining a set of probabilistic scenarios related to this expectation. To establish the probability of the base case scenario P_0, the error in the prediction is assumed to be Gaussian and the error function is utilized to calculate the probability as

$$P_0 = \mathrm{erf}(\frac{B_0 \cdot P_{g,\max}}{\sigma\sqrt{2}}),$$

where $P_{g,\max}$ is the maximum power generation capability of the wind farm, B_0 is the width of the band (in percentage of $P_{g,\max}$) over which the base case scenario is presumed to be an accurate prediction, and σ is the standard deviation of the stochastic prediction of the wind farm generation.

The non-base-case scenarios are characterized by selecting a confidence interval step size P_{step}, and subsequently utilizing the inverse error function to determine the deviation from the expected generation for the probability interval for a given scenario as

$$n_s = \sqrt{2} \cdot \mathrm{erf}^{-1}(P_0 + m_s \cdot P_{step}),$$

where the inverse error function yields that the variation in the wind farm generation output will fall within n_s standard deviations of the expected value with a probability of $P_0 + m_s \cdot P_{step}$, and m_s is an integer multiple of P_{step}. This procedure is completed for all scenarios, such that a discrete set of potential stochastic variations in generation and their corresponding probabilities are determined, as shown in Fig. 2.

This characterization of the renewable generation uncertainty yields the set of weighting probabilities P_s which are utilized in the cost function (9), and the corresponding variations in generation output. This probabilistic characterization can only be utilized effectively as an optimization input if there is a resource within the system which can respond to such variations.

For this case, the distribution network responds to the variable windpower output through the provision of vehicle-to-grid reserve.

The two-tier reserve system used here places additional constraints on the optimization algorithm in order to govern the reserve purchasing, where the set of constraints

$$RC_0 = RC_s, \quad s = 1, \ldots, N_S$$

is included to ensure that the amount of reserve capacity purchased RC_s is identical in all scenarios. The rationale behind this constraint set is that in order for this reserve capacity to be available in any of the scenarios, it must be purchased in advance, and thus its cost must be incurred within all scenarios regardless of whether the reserves are deployed. Alternatively, balancing reserve can be purchased in real-time on a per-scenario basis at an elevated cost. This adds no inter-scenario constraints, but places a financial penalty on utilizing balancing reserves.

With the costs and constraints of the two-tier reserve system defined, the optimization seeks to determine the reserve purchase schedule which will maximize the expected profit. When accounting for stochastic variation in generation, the expanded optimization will maximize the expected benefit through a blend of reserve purchases from within the two-tiers.

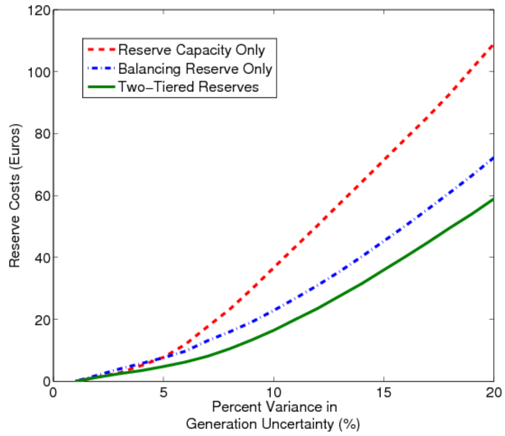

Figure 3: Comparison of expected cost of reserve acquisition with varying accuracy of wind power forecast. The case displayed here shows the cost comparison for a 5:1 price ratio between balancing reserve and reserve capacity.

An example case utilizing the stochastic optimization is displayed in Fig. 3, where the cost of reserve purchases is shown relative to variance in the wind generation forecast. It is apparent that a decrease in the accuracy of the predicted renewable generation is equivalent to an increased variance in the prediction, which inevitably leads to an increase in reserve purchase costs. However, from this example it is seen that when stochastic optimization is applied to determine the blend of reserve purchases, the resultant cost is always less than or equal to the cost of purchasing either of the two types of reserve exclusively.

Given that the stochastic optimization yields the optimal reserve schedule which addresses the generation uncertainty, it can be helpful to observe the variation in the cost of reserve purchases against a number of control variables. Figure 4 displays the total expected cost of the two-tier reserve purchases against both the variance in the predicted wind generation and against the ratio of the cost of the balancing reserve to reserve capacity. The expected cost of reserve is seen to increase in a nonlinear monotonic fashion with increasing variance in generation, owing to the increased likelihood of reserves being deployed. As the cost ratio of real-time balancing reserve to reserve capacity increases, the expected cost of reserve purchases increases monotonically, but approaches an asymptotic value as the relative cost of balancing reserve becomes prohibitively expensive, and the optimization favors the pre-purchase of reserve capacity.

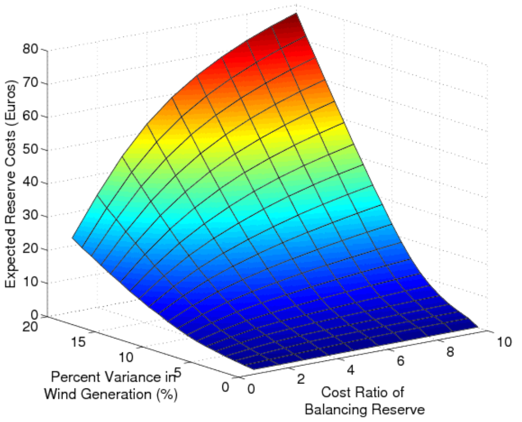

Figure 4: Expected total reserve costs obtained through stochastic optimization of the two-tier reserve purchases. For a given expected generation forecast, the variation in expected cost is shown against changes in both pricing of reserves and accuracy of the forecast.

CONCLUSIONS

This paper has addressed the use of a two-tier distribution network reserve structure to address uncertainty in distributed generation. An optimization method was proposed where a network is first analyzed to determine if there are any potential nodes or lines in the network which may potential lead to constraint violations. The network was then reduced in such a manner that these potentially-binding constraints and the associated aggregated network are then used in a reduced order optimization. The uncertainty in the distributed renewable generation sources is characterized and implemented in optimization as a set of parallel probabilistic scenarios, with a cost function designed to minimize expected costs. For the example demonstrated here, there was a potential shortage of wind generation, and the expected costs were minimized through the purchase of two variants of vehicle-to-grid reserves. It was demonstrated that this two-tier reserve structure leads to a reduction of the expected reserve purchase cost. Additionally, the effects of forecast accuracy and reserve pricing were demonstrated.

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