PROBABILISTIC ASSESSMENT OF CONSTRAINT VOLUMES ON ACTIVE NETWORKS

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ABSTRACT

Active Network Management (ANM) presents an effective approach to facilitating the connection of renewable generation onto increasingly congested networks. Estimating the severity of constraint experienced by managed generators is a key requirement in order to successfully evaluate the impact of implementing ANM solutions. This paper describes an established method of constraint analysis, its requirements, and outcomes. This approach to constraint analysis is developed further, introducing a probabilistic method for the estimation of curtailment volumes. Examples are provided illustrating the outcomes from such studies.

INTRODUCTION

Distribution networks worldwide are increasingly under strain as growing numbers of generators require connection. The technical issues which arise due to the emergence of distributed generation (DG) have been well documented [1]. Traditional methods of overcoming such barriers to connection are based around the reinforcement of network infrastructure, providing an increase in network capacity and unconstrained connection of DG.

Traditional worst-case-scenario planning approaches may be viewed as unnecessarily conservative as in practise limits may rarely be breached. This is further accentuated if DG is intermittent. The exploitation of “active” control philosophies, which manage the output of DG under network constraint conditions, is considered a viable alternative to the expensive reinforcement of network infrastructure [2].

Within the assessment procedure for ANM deployment, it is important to gauge the severity and frequency of control actions required to manage network constraints. For scenarios in which the network is heavily constrained, it may prove more favourable to make the expensive investment in network reinforcement, rather than experience significant energy curtailment of managed generators within an ANM scheme.

Constraint analysis estimates the frequency and magnitude of constraint events expected to arise due to the connection of DG. From this it is possible to approximate the energy curtailment that actively-managed DG will experience. This paper describes an established constraint analysis methodology before presenting further developments which utilise probabilistic techniques to bring added flexibility and functionality to the analysis. This novel approach provides the user with a more informative range of results when compared to the initial time-series approach.

TIME-SERIES ANALYSIS OF NETWORK CONSTRAINTS

The objective of constraint analysis is to determine the frequency and magnitude of constraint events. In the context of ANM, constraint events can be described as periods during which energy export from actively-managed DG must be curtailed to ensure power flows or voltages do not breach limits. In the time-series approach, curtailment volumes are calculated by performing successive discrete calculations using input data representing average values of network parameters over time-steps, such as half-hourly or hourly intervals for the defined study period.

ANM Scheme Specification

Identification of Constraint Locations

It is initially necessary to identify the constraints that will occur on the network, which are typically thermal power flow limits or voltage limits. This is achieved by performing load flow studies on the network, examining results under extreme conditions: maximum DG output and minimum demand; minimum DG output and maximum demand.

Principles of Access (PoA)

The PoA specify the manner and order in which managed DG will be curtailed so as to maintain the network within operating limits [3]. Specification of PoA is required to ensure curtailment levels are estimated accurately.

Data Requirements

Time-Series Data Profiles

In order to calculate curtailment, time-series data profiles are required for all generators and loads connected to the network. The time series profiles must be complete, with data for all parameters available at each time-step. As there are correlations between certain parameters, it is important that all profiles are temporally synchronized, i.e. they represent the same historical period.

Historical time-series data will not be available for DG which has yet to connect to the network. Forecasting of such profiles can be a challenge when the DG output is influenced by intermittent factors, such as wind speed. In this case it is necessary to synthesise a time-series profile using other available data. This can be performed through the scaling from the historical profile of an existing local generator of a similar type. For wind DG, a profile can be created by mapping local wind speed measurements to the generator's wind-speed/output curve.

Sensitivity Factors

It is necessary to identify sensitivity factors which characterise the relationship between DG export, local demands, and their contribution to the constraint locations. Although the relationships may be non-linear in practise, for the purposes of constraint analysis it is reasonable to assume that sensitivity factors can be represented by a single-value. In a scenario where a DG unit does not contribute to a constraint location, the sensitivity factor will be zero. The inverse of this multiplier represents the scaling factor by which generation must be curtailed in order to reduce the power flow or voltage at a constraint location. Sensitivity factors are required for all generators and loads on the network.

Constraint Limits

The limits of network operation, typically power flow and voltage, must be identified for the analysis to identify constraint events. Line capacity limits may be seasonal in the case of overhead conductors; voltage limits may depend on demand levels at any given time. If dynamic line rating technology is utilised within the ANM scheme, the line capacity limits will fluctuate to reflect the changing rating of the conductor as local meteorological conditions vary. In accordance with the operational characteristics of ANM schemes, operating margins will be put in place to define the trigger levels for control action.

Curtailment Calculation Process

It is not the purpose of this paper to provide a detailed description of the curtailment calculation methodology; however, a brief overview of the process is given. In order to determine curtailment at a single time-step, it is first necessary to calculate the power flow or voltage at each constraint location. This is calculated using the DG export and local load values, with their contributions to the constraint location scaled using the sensitivity factors. Alternatively, if necessary, the constraint analysis will run load flow solutions for every time-step. In the event that overloads are identified, DG that contributes to the constraint is curtailed in an order that reflects the Principles of Access. The DG curtailment required to eliminate the overload or over-voltage is calculated using the inverse sensitivity factors, scaling the reduction in DG output required. This calculation is repeated at each constraint location, taking account of the interactive nature of multiple constraints.

Estimating Annual Curtailment

The curtailment calculation described in the previous sub-section determines the required curtailment, if any, for a single snapshot in time. It is the aim of the constraint analysis to calculate the curtailment behaviour over a period, such as a year. The curtailment calculation is performed for each time-step in the parameter profiles to provide a wider picture of constraint behaviour across the study period. This approach will provide a rough illustration of the magnitude of curtailment which will be necessary; however it must be noted that this is only an estimation, based upon the historical study period across which the input data is measured. If extensive time-series data is available, constraint analysis may be performed across several years, to examine how constraints may vary between different study periods.

PROBABILISTIC CONSTRAINT ANALYSIS

The time-series approach to constraint analysis has inherent limitations which can be overcome through the application of probabilistic techniques.

Motivation

The main limitations in the time-series constraint analysis relate to the data requirements for undertaking a study. The requirement for complete time-series data, for all parameters, at regular intervals during the study period, will in many cases result in a lack of sufficient data to undertake analysis over an adequate time period. Performing a study with limited data can present misleading results; if it is only possible to perform a study across a short period of time, then the outcomes are only representative of constraint levels over a small sample of potential constraint behaviour.

This highlights a general limitation of time-series analysis; that the outcome of such a study will only reflect the specific combination of generation and load levels that have occurred over the historical study period. It may be that there are many more potential combinations of DG output and load that may result in constraint conditions.

Probabilistic techniques take account of the uncertainty in the output of intermittent DG and load levels, studying the outcome of numerous combinations of the varying parameters. The strict data requirements that exist for time-series constraint analysis are relaxed for a probabilistic study, as is explained in the following sections.

Fundamental Theory

The use of probabilistic methods for constraint analysis requires the representation of variable network parameters, such as demand and generation, as probabilistic functions rather than empirical time-series profiles. This shift removes the temporal representation of parameters therefore overcoming the limiting requirements regarding temporally concurrent input profiles. Correlation between profiles can still be represented, as discussed below.

To determine constraint behaviour, the Monte-Carlo sampling technique is applied; a proven method of approximating the solution of a function using probabilistic inputs. This method extracts a sample from each of the probabilistic functions. The samples replace the time-series inputs from the previous constraint analysis procedure. The curtailment calculation is repeated for a very large number of samples, and the results will converge towards a sample average approximation. This single-point estimate can be scaled to present an approximation of constraint volumes across any period.

METHODOLOGY

The detailed procedure for undertaking probabilistic constraint analysis is best described divided into three segments: the preparation of data; the curtailment assessment procedure; and the analysis and reporting of results. These segments are described in further detail, and the methodology illustrated in Figure 1.

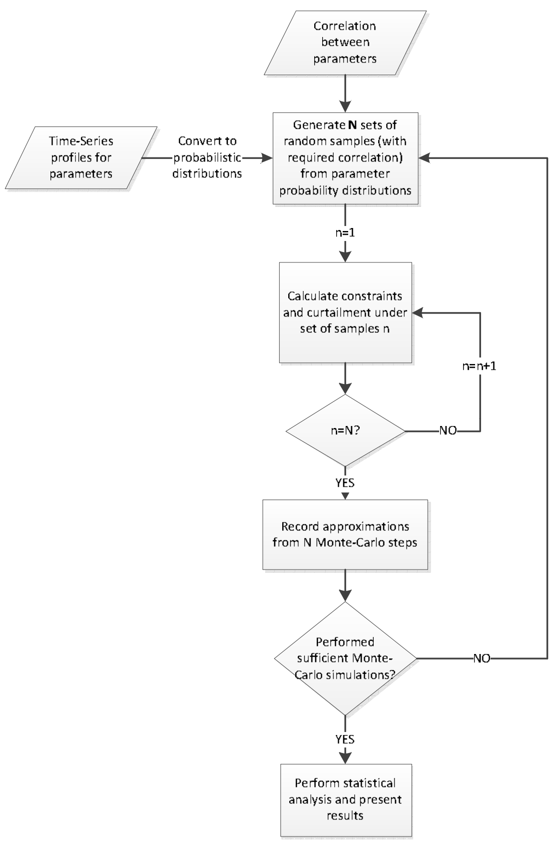

Figure 1: Probabilistic constraint analysis methodology

Data Preparation

The probabilistic constraint analysis procedure requires input data, previously presented as time-series profiles, to be represented as a probability density function (*pdf*). The *pdf* represents the likelihood at any point in time that a parameter will be a certain value. Each *pdf* can be generated from measured historical data, or from a forecast of future parameter behaviour. If dynamic line ratings are employed, the capacity limits on the monitored lines are also represented as a *pdf*. The probabilistic functions are based upon some form of data profile, most likely time-series, though there are no firm requirements regarding its nature. However, as expected, the larger the initial dataset from which the probabilistic profile is derived, the more representative it will be of the parameter characteristics. The *pdf*s are transformed into cumulative distribution functions in preparation for the sampling process to follow.

Assessment Procedure

The assessment procedure implements the Monte-Carlo simulation method, approximating the constraint and curtailment behaviour based on the *pdf*s representing the network parameters. The first step of the simulation is to generate a large number of samples, *N*, to represent values of each probabilistic parameter. The samples are extracted from cumulative distribution functions (*cdf*), which represent each probabilistic parameter, using a technique such as inverse transform sampling [4].

This sampling procedure results in the generation of a set of ***N*** independent samples for each parameter. In practise, correlation will exist between network parameters, they may not be independent from each other. For example, the level of wind output and local demand may be correlated as both are influenced by meteorological conditions, as will dynamic line ratings. Correlation can be incorporated within the sampling procedure through the use of a correlation coefficient. The correlation coefficient is used to generate pseudo-random correlated numbers which are used to sample from the *cdf* in the inverse transform sampling procedure. When applied, this results in the required correlation between parameter samples.

The process for calculating the constraint and curtailment levels at a single snapshot is the same as the time-series constraint analysis. This procedure is repeated for all ***N*** samples, with constraint volumes calculated at each sample step. The sample average, at ***N***, for curtailment volumes represents the average curtailment at any point in time. Annual approximations for constraint and individual DG curtailment (in MWh) are simply calculated by multiplying the respective sample averages by 8760 (number of hours in a year).

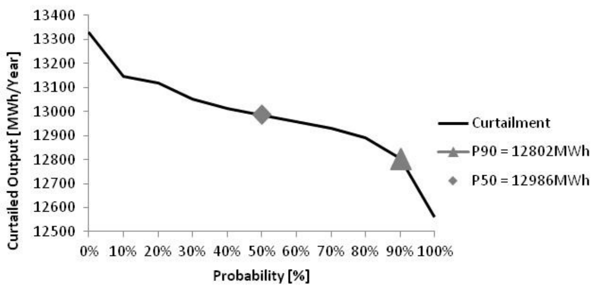

Figure 2: Cumulative curtailed DG output

Reporting Results

It is possible to only perform the probabilistic analysis procedure once, with a sufficiently high value of N that ensures that the study converges towards a single-point estimate for curtailment volumes. This will provide a similar type of result as in the time-series studies; a single approximation for the overall constraint volumes (in MWh). Further detail can be extracted, however, by performing multiple studies, re-sampling at each iteration, with a smaller value of N, to provide a range of possible outcomes. As the value of N is not as large as for a single study, each approximation will not converge to the same accuracy, resulting in a wider range of curtailment volumes. This may provide a more accurate representation of the variability in network behaviour, and thus potential constraint activity, between study periods.

From the outcomes of multiple studies it is possible to calculate probability percentiles, such as the P-90 figure. P-90 presents the 90% confidence interval for the minimum curtailed output volumes to be experienced. Similarly, the P-50 figure presents the sample median approximation across all studies. Figure 2 presents an example of the cumulative probability plot of curtailed export from actively-managed DG, illustrating the P-90 and P-50 points. Frequency analysis of the uncurtailed and curtailed outputs from DG is shown in Figure 3. This examines the extent of curtailment across the multiple Monte-Carlo studies performed.

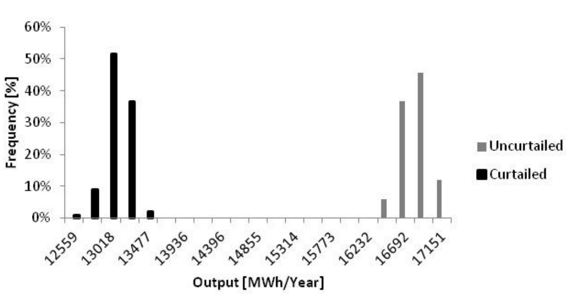

Figure 3: DG export frequency analysis

CONCLUSIONS

The probabilistic constraint analysis approach presented within this paper increases the flexibility and applicability of such studies. The flexible data requirements for probabilistic study overcomes some of the limitations which exist in the time-series based approach. The results offered by probabilistic analysis present a more varied and detailed approximation of constraint behaviour and curtailment volumes than the time-series approach.

Constraint analysis plays an important role in the assessment of ANM feasibility. The analysis offers approximations of constraint magnitudes at the constraint locations, the overall curtailment of actively-managed DG, and the curtailment experienced by DG due to individual constraint locations. This information provides DNOs and generation developers with a detailed picture of constraints on the network, and how they may impact the behaviour of actively-managed DG.

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