REQUIREMENTS-DRIVEN DISTRIBUTION STATE ESTIMATION

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ABSTRACT

This paper describes the development of distribution state estimation for trial on the Orkney Isles in the north of Scotland. The paper discusses the techniques selected for the trial based on the requirements of the distribution network operator. The techniques include the use of a novel error estimation technique that calculates an error interval for data derived via distribution state estimation.

INTRODUCTION

The proliferation of distributed energy resources (DER) and anticipated changes to load patterns are changing the planning and operation of distribution networks. Issues associated with the connection of DER, such as congestion, voltage-rise and voltage-step-change, have led to the requirement for greater visibility of such networks. However, the need for visibility has to be balanced against the cost of additional measurement and telemetry, including possible redundancy. Distribution state estimation (DSE) offers the possibility of using a reduced set of measurements, augmented with pseudo-measurements, to provide extended visibility of distribution networks. As a result, Scottish and Southern Energy Power Distribution (SSEPD), the Distribution Network Operator (DNO), is trialling the use of DSE on the Orkney Islands in Scotland, an area of network with significant connection of distributed generation and additional yet untapped renewable energy resources. This activity is set in the context of the wider deployment of an active network management scheme on Orkney, which has been operational for three years and has enabled an additional >20 MW to connect to a network previously considered full [1], representing one of the leading smart grid deployment projects in Europe. DSE is one of the further developments being implemented in the next generation of the active network management scheme on the Orkney Isles [2].

In this paper, we discuss the DNO's requirements for distribution state estimation and the techniques which were selected based on those requirements. During the requirements elicitation process, a requirement emerged for an online method for computing the error bounds of the state variables estimated by the DSE and additional quantities derived from those estimates, e.g. current and power flow. This requirement has yet to appear in the literature on DSE but received consideration in research into classical state estimation problems.

For the Orkney Island trials, the problem of error estimation was address by adapting the method originally presented in [3][4] and augmenting the functionality of SGS's existing distribution state estimator, **sgs visibility**, to utilize that adapted method. The method exploits the full measurement Jacobian for a converged state estimate and the measurement residuals, as produced by **sgs visibility**, as well as knowledge of the transducer errors. This paper discusses the nature of further results and the validity of the assumptions on which the method is based. The impact of error estimation on the use of the output of distribution state estimation, as a tool for supporting network operation and as a potential input to active network management, is also discussed.

DISTRIBUTION STATE ESTIMATION

DSE has been the subject of numerous papers [5-13]. DSE problems differ from classical state estimation problems in that the limited number of measurements renders most DSE problems mathematically under-determined.

Whilst [5-13] illustrate several different formulations of distribution state estimation problems, the DSE techniques discussed in this paper are based on weighted least squares (WLS) methods which involved providing the state estimator with additional pseudo-measurements, in our case estimates of load, which render the state estimation problem over-determined and hence tractable using more traditional state estimation methods. Our selection of state estimation method has been influenced by the results reported in [13].

DSE ON ORKNEY

The Orkney Isles, to the north of the Scottish mainland, are an area of considerable reserves of renewable energy. The islands rank amongst the windiest places in Europe, where the capacity factor of wind generation regularly exceeds 40%. The area also hosts the European Marine Energy Centre, with significant wave and tidal resource in the waters around the island. In the mid-2000s the network on Orkney had reached capacity for connection of distributed generation. In order to avoid prohibitively expensive reinforcement of the submarine cable connections to the mainland, an active network management scheme was deployed on the island to manage connected generation under non-firm connection agreements [1][2].

Constraints on the network are primarily thermal; however, the increasing level of penetration of distributed generation is expected to present voltage control challenges and the relatively observable nature of the network make it an attractive site for the trials of DSE. It is an area of network which is planned and operated in an active manner and, as a result, greater visibility of the network would be beneficial to the DNO. SSEPD wishes to trial the use of DSE on Orkney to assess its performance and potential application for other locations in its licence areas. It is expected that the deployment of DSE on an existing active network management platform will further demonstrate a least cost and efficient means of deploying smart grid functionality.

The network on Orkney is reasonably well instrumented. The network model used by the DSE comprises 70 buses with 76 branches. Voltage at 15 of the busbars is visible to the control room, as are flows or current on 30 of the branches. Studies carried out by Smarter Grid Solutions have shown that DSE, without employing pseudo-measurements, increases the observability index of the network from 25.86% to 83.56%. The addition of a small number of pseudo-measurements can increase observability to 100% at 33 kV and at primary substations (33/11 kV).

DSE Requirements

Initial trials are to focus on the 33kV network and 11kV primary substations. SSEPD has identified the requirement for:

- Security, capacity, performance, availability, and configurability;
- The ability to identify areas of the network where a state estimate can be calculated;
- The identification of bad/erroneous data;
- The ability to provide an estimate of the error in the resulting state estimate; and
- Timely production of state estimation data;

Most of the requirements above can be met with techniques available in the literature on DSE. Below we detail our selected methods and the rationale for their selection. Error estimation is given special treatment in that we have selected a technique not normally applied to distribution networks. We present the results of offline studies based on historical data to indicate the sort of performance we expect to see during online DSE trials.

DSE Methods

Observability Analysis

Observabililty analysis involves identifying observable islands, contiguous sets of buses for which, given the available measurements and pseudo-measurements, a state estimate can be calculated. **sgs visibility** uses a numerical method based on Gaussian elimination, similar to the method described in [14].

State Estimation

For each observable island a state estimate is calculated. **sgs visibility** employs the Hachtel method for state estimation [15]. In the Hachtel method, virtual measurements and regular measurements are represented as equality constraints. This leads to increased numerical stability of the state estimator as the coefficient matrix is less likely to be ill-conditioned.

Bad Data Detection

Once a state estimate for an observable island has been calculated, **sgs visibility** uses the maximum normalised residual technique for identifying bad data [15]. Should bad data be identified, it is removed and the DSE process is started again with the reduced data set omitting the offending measurand/pseudo-measurement. New observable islands are identified, state estimates for each island are calculated and bad data detection repeated. This process is executed recursively until the DSE has found a set of state estimates for a set of observable islands with no bad data.

Error Estimation

SSEPD requires a means of estimating the error of the output of the state estimator. This is a novel facet of the DSE being deployed on Orkney. As a result we have described the approach in the following section.

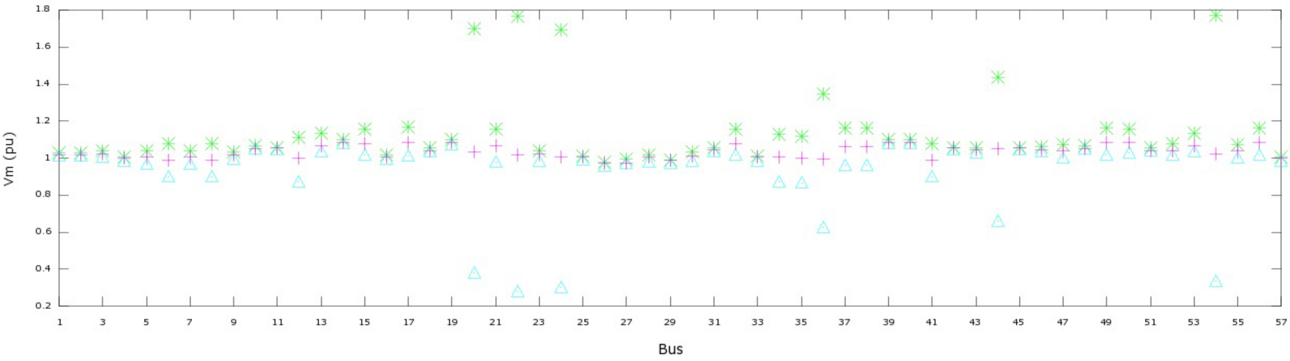
ERROR ESTIMATION

The error estimation module of **sgs visibility** uses the method described in [3][4]. The method determines the maximum and minimum possible error in individual estimated states, i.e. bus voltage magnitude and angle, based on the solved measurement Jacobian, transducer errors and measurement residuals. A set of optimisations are solved for each state variable or quantity derived from state variables that we wish to calculate an upper and lower bound for, e.g. branch flows.

The objective functions of the method can be expressed as follows,

$$Max: dx_i \quad i \ \forall \ N-1$$
$$Min: dx_i \quad i \ \forall \ N-1$$

where dx_i is the change in the *ith* state variable for N state variables. For a given solved island of N buses the error bound calculation entails 4N-2 calculations.



+ - estimate, *-upper bound, Δ - lower bound

Figure 1: Voltage magnitude state variable estimates and calculated error bounds.

The problem is formulated as a linear programme, with 2N-1 calculations to determine the minimum possible bounds and another 2N-1 calculations to determine the maximum possible bounds. The slack bus has a reference angle of 0 radians and hence no error bound calculation is required for the slack bus angle.

For any given measurement, there will be a measurement error, owing to the calibration and specification of the transducer employed, given as τ. This is taken account of by adding and subtracting τ to and from the residual, i.e. the difference between the measured states and the estimated states,

$$\Delta z_j = z_j - h(\hat{x}) \pm \tau_j$$

where Δz_j is the residual associated with the jth measurement and $h(\hat{x})$ is the calculated (expected) values for the various measurements arising out of a converged state estimate solution. The resulting vectors of m values are given as Δz^l and Δz^u . These values are the upper and lower bounds of the inequality constraints in the formulation. In the case of virtual measurements there is no transducer error, i.e. τ=0. The full measurement Jacobian contains the sensitivity of each of the measured quantities, including virtual measurements, to changes in the estimated state variables. The set of inequality constraints relating to these quantities can be expressed as follows,

$$\Delta z^l \leq H(x)\Delta x \leq \Delta z^u$$

where $H(x)$ is the full measurement Jacobian obtained from the converged solution of the state estimator and Δx is the vector of changes in state determined by the linear programme, commonly referred to as the control or decision variable. For each iteration the state being maximised/minimised (i) is incremented by one, i.e. for any given solution to the linear programme, it is only the change in the ith state (dx_i) that is of relevance. Values are calculated for all other states, but these values are adjusted by the linear programme as necessary to achieve the maximisation or minimisation of the *ith* state.

Figure 1 shows a set of results for the largest observable island on Orkney without using pseudo-measurements.

Implicit in this method is the fact that states in the network for which there are no or very few associated measurements of any kind, the error bounds will be significant and will generally represent an accumulation of the transducer errors. This can be seen in the outliers in figure 1, at bus 20, 22, 24, 36, 44, and 54. These buses are located on remote parts of the network, each one being four to five buses away from a measurement. Studies indicate that pseudo-measurements can tighten these bounds. The sparsity of the $H(x)$ is also of relevance here. For weakly interconnected systems, it will tend to be sparse, essentially providing less restriction on the error bounds. Simply put, each value in $H(x)$ relates a measurement to a state, the less non-zero entries the less information available on the unmeasured states, of which typically there are many.

Another point to note is the assumption of linearity around a given operating point. In [4], two formulations of the error estimation problem were compared: one based on a linearised model solved using linear programming and a non-linear formulation solved with computationally more intensive quadratic programming. The results in were comparable; however, it may be possible that weights and corresponding τ of any pseudo-measurements would challenge the linearity assumption. Further investigation in this area is required, with potential for the application of non-linear programming techniques.

In terms of time to compute a solution, the method set out in [3][4] requires a significant number of linear programmes to be solved in order to calculate state estimates. For a network the size of Orkney, this takes around 2 seconds on a standard server. However, given that each linear programme is independent, these could be solved concurrently on different cores of the server, reducing the time to compute a solution.

DSE AND ANM

As discussed at the start of the paper, Orkney hosts one of the leading smart grid deployments in Europe. The ANM scheme on Orkney has been in operation since 2009. Whilst the ANM scheme on Orkney does not utilise DSE, the proposed use of DSE within the context of ANM is not new: GenAVC [16] exploited DSE to reduce measurement costs. AuRA-NMS [17], which tackled both voltage and thermal issues, also proposed the use of DSE to those ends but no trials were ever undertaken as part of that project even though several approaches to DSE were developed.

The rationale, that the primary reason for deploying DSE as part of an ANM scheme is to reduce instrumentation costs and/or improve performance in the presence of measurement errors or loss of communications, is one that researchers continue to wrestle with. The cost and performance implications for DSE have to be compared with the cost and performance implications of additional measurements.

CONCLUSIONS

This paper has discussed the requirements driving the development of DSE on the Orkney Isles in Scotland. Based on those requirements, the methods described in this paper have been selected for trials which are due to begin in the summer of 2013.

The error estimation technique has been highlighted as a requirement of the DNO if DSE is to be successfully applied. This paper has investigated the use of the technique described in [2][3] to this end. The technique is based on a number of assumptions, mainly that the validity of the assumption that linearity can be assumed across the ranges considered by τ and that no specific treatment of parameter errors, i.e. error in the assumed branch parameters, is considered. It is anticipated that the forthcoming trials will provide data that will be used to assess the impact of these assumptions and will be of great interest to the wider power industry working on these issues.

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