IMPROVING STATE ESTIMATION ACCURACY FOR ACTIVE NETWORK MANAGEMENT USING ADVANCED MODELLING TECHNIQUES

Weicong KONG
University of Strathclyde – UK
weicong.kong@gmail.com

David TC WANG
Smarter Grid Solutions – UK
dwang@smartergridsolutions.com

Colin FOOTE
Smarter Grid Solutions – UK
cfoote@smartergridsolutions.com

Andrea MICHIORRI
Smarter Grid Solutions – UK
amichiorri@smartergridsolutions.com

Martin LEE
Scottish & Southern Energy – UK
martin.lee@sse.com

David MacLEMAN
Scottish & Southern Energy – UK
david.macleman@sse.com

ABSTRACT

State estimation is considered for application to the 33 kV distribution network on the British Orkney Isles. One immediate challenge is the insufficient real-time measurements available to make the network completely observable. In this paper, four pseudo-measurement modelling methods are used to improve the accuracy of weighted least squares state estimation. The results show that although no method can guarantee to produce the most accurate state estimates at every location, overall using advanced techniques such as correlation and Gaussian Mixture Modelling yields more accurate results than using simpler methods. Moreover, the presence of distributed generation can cause extremely high percentage errors in power flow estimates, giving misleading information about the ideal location for new measurements.

INTRODUCTION

Scottish and Southern Energy (SSE) has established an active network management (ANM) scheme for the distribution network on the Orkney Isles. Generation from participating wind farms is curtailed whenever necessary to prevent any circuit overloading. By receiving signals in real-time about loading conditions of the monitored circuits, an ANM controller designed by Smarter Grid Solutions Ltd. (SGS) calculates the amount of generation that needs to be curtailed. The ANM scheme is allowing considerably more wind farms to connect to the network without significant reinforcements. For further development of the ANM scheme, the scope for applying state estimation (SE) is being investigated. This could improve the reliability of the existing monitoring system and also allow more power system quantities (e.g. bus voltages and power flows) to be measured without installing additional transducers. A load flow solution obtained by SE for the whole network can also be used to test new methods of network management and control.

One immediate challenge of applying SE is that there are insufficient real-time measurements to make the network completely observable. Pseudo-measurements are required to provide an estimation of demand at some locations. To limit the degradation of the SE results due to the use of pseudo-measurements, advanced load modelling methods can be used.

In earlier work the errors of pseudo-measurements were simply assumed by the authors [1, 2] to be much greater than those of real-time measurements, while later more advanced methods were introduced to generate more accurate pseudo-measurements. Ghosh *et al* [3] showed that loads can be modelled more accurately using a beta distribution rather than a normal distribution; however, the beta distribution cannot be used for a weighted least squares (WLS) based SE. Mantisas *et al* [4] proposed two methods to model pseudo-measurements; one was based on analysing the correlation between real-time measurements taken at substations and load pseudo-measurements, while in another approach the accuracy of the load pseudo-measurements was improved through Gaussian Mixture Modelling (GMM). The results showed that both approaches improved the SE accuracy on a 14-bus distribution network to a similar degree. In [5], an artificial neural network (ANN) algorithm was adopted to generate pseudo-measurements that temporarily replace the real-time measurements lost during contingent events. However, the pseudo-measurements obtained this way require the prior knowledge of the real-time measurements immediately before the fault rather than a historical load profile.

Despite advanced methods being used, little has been reported on how much improvement in SE accuracy can be achieved compared with using simpler methods, therefore the incentive for adopting advanced methods is not clear. This paper compares four different methods to find the most suitable one for SE on the Orkney network.

STATE ESTIMATION ALGORITHM

Each measurement input contains a certain degree of error that can be expressed using the following equation:

$$\boldsymbol{e} = \boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x}) \tag{1}$$

where $\boldsymbol{e}$ is a measurement error vector, $\boldsymbol{z}$ is a measurement vector, $\boldsymbol{x}$ is a system state variables vector, and $\boldsymbol{h}$ is a nonlinear measurement function vector. In the weighted least squares method [6], $\boldsymbol{x}$ is calculated that minimises the square of the error vector $\boldsymbol{e}$; the objective function is formulated as follows:

$$J(\boldsymbol{x}) = [\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x})]^{\mathrm{T}}\boldsymbol{R}^{-1}[\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x})] \tag{2}$$

where $\boldsymbol{R}$ is a diagonal error covariance matrix that gives a weighting to each measurement error based on the variance σ^2 of the measurements:

$$\boldsymbol{R} = \begin{bmatrix} \sigma_1^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_m^2 \end{bmatrix} \quad (3)$$

where m is the total number of measurements used for SE. The state variable vector $\boldsymbol{x}$ can be obtained by solving the following linearised derivative of (2) iteratively:

$$\boldsymbol{H}^T(\boldsymbol{x}_k)\boldsymbol{R}^{-1}\boldsymbol{H}(\boldsymbol{x}_k)\Delta x_{k+1} = \boldsymbol{H}(\boldsymbol{x}_k)^T\boldsymbol{R}^{-1}[\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x}_k)] \quad (4)$$

$$\Delta \boldsymbol{x}_{k+1} = \boldsymbol{x}_{k+1} - \boldsymbol{x}_k \quad (5)$$

$$\boldsymbol{H}(\boldsymbol{x}_k) = \frac{\partial \boldsymbol{h}(\boldsymbol{x}_k)}{\partial \boldsymbol{x}_k} \quad (6)$$

where k is an iteration number index. Here, a variant of the WLS-based SE was used, which formulates zero power-injection measurements as constraints [7]. As a result the numerical stability when solving the equations can be further improved.

LOAD MODELLING METHODS

Method of Assumed Variance and Normal Distribution Fitting

Given a historical load profile, the pseudo-measurement value μ is calculated:

$$\mu = \frac{1}{n}\sum_{i=1}^{n}\alpha_i \quad (7)$$

where α_i, is the i^{th} sample of the load variable $\boldsymbol{\alpha}$ and n is the size of samples taken from the historical data. In the method of assumed variance (AV), the variance σ^2 of the pseudo-measurement is simply calculated based on an assumed arbitrary percentage δ, in this paper δ is set to 50% and fixed for all the pseudo-measurements:

$$\sigma^2 = \delta \cdot \mu \quad (8)$$

Similar to the AV method, the method of normal distribution fitting (NDF) yields the measurement value μ obtained using (7). However, the variance σ^2 is calculated using the conventional statistics equation:

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(\alpha_i - \mu)^2 \quad (9)$$

Gaussian Mixture Modelling

Unlike NDF, Gaussian mixture modelling (GMM) calculates a multi-component PDF that consists of multiple normally distributed sub-PDFs (mixture components), as depicted in Figure 1. The multi-component PDF ($f(\boldsymbol{\alpha})$) is expressed as:

$$f(\boldsymbol{\alpha}) = \sum_{i=1}^{N_c} w_i f(\boldsymbol{\alpha}|\mu_i, \Sigma_i)$$
$$subject\ to: w_i > 0 \text{ and } \sum_{i=1}^{N_c} w_i = 1 \quad (10)$$

where N_c is the number of mixture components, w_i is the weight of i^{th} mixture component. $f(\boldsymbol{\alpha}|\mu_i, \Sigma_i)$ is the i^{th} mixture component given by:

$$f(\boldsymbol{\alpha}|\mu_i, \Sigma_i) = \frac{1}{(2\pi)^{\frac{1}{2}} det\,(\Sigma_i)^{\frac{1}{2}}} e^{-\frac{1}{2}(\alpha-\mu_i)^T\Sigma_i^{-1}(\alpha-\mu_i)} \quad (11)$$

where μ_i is the mean of i^{th} normal mixture component, and:

$$\Sigma_i = E[(\boldsymbol{\alpha} - \mu_i)^T(\boldsymbol{\alpha} - \mu_i)] \quad (12)$$

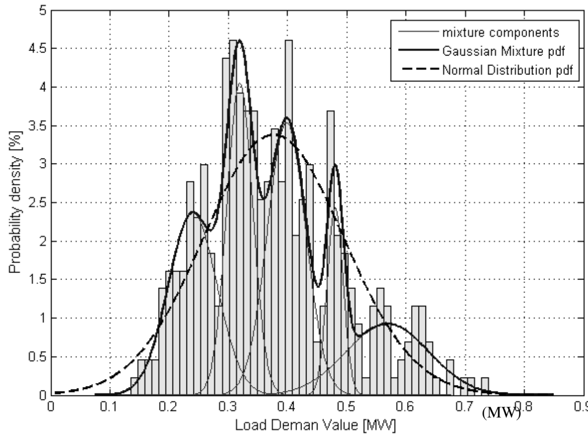

Figure 1: Normal distribution and Gaussian mixture models

The pseudo-measurement value μ is equal to the mean of the normal mixture component closest to the estimated demand, while σ^2 is set to the variance of the normal mixture component.

Correlation Method

The method of correlation seeks the linear numerical relationship between a power system quantity X that is real-time measured and a load Y by analysing the historical data:

$$cov(X,Y) = E[(X - \mu_x)(Y - \mu_y)] \quad (13)$$

where μ_x and μ_y are the means of X and Y. In the error covariance matrix $\boldsymbol{R}$, the element that corresponds to the real measurement of X and the pseudo-measurement of Y is set equal to the calculated covariance. The covariance coefficient, which has a range between -1 and 1, is then derived:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X\sigma_Y} \quad (14)$$

where σ_X and σ_Y are the standard deviation of X and Y respectively. The closer the correlation coefficient to its extreme values, the more linear is the relationship between X and Y. Linear regression analysis is applied considering the covariance coefficient to find out the degree of dependency between the non-monitored load and the real measurement. A regression line is then found that represents the linear relationship between the two variables. The measurement value μ therefore lies on the regression line and the standard deviation σ can be obtained based on the samples and the regression line.

RESULTS

The 33 kV distribution network on the Orkney Islands is depicted in Figure 2. There are 16 loads connected to the network via 33/11 kV transformers. The network has one of the highest penetration of wind generation in the UK. As the total generation exceeds the total demand on Orkney, power is exported to the mainland transmission network via two sub-sea cables (lines 18 and 38). It is assumed here that all 16 loads are unmonitored and modelled as pseudo-measurements.

Generic hourly historical load profiles for 2008 and 2009 [8] were used to conduct the study. The load data in 2008 was used for modelling the pseudo-measurements. The load data in 2009 was regarded as the true demand values and used for running load flow analysis to compare the results with those of SE using the pseudo-measurements at the same time stamp. In this study an hourly interval between each time stamp is considered and the period of study is confined to the winter season from December to January.

Error! Reference source not found. shows the average rror of (a) voltage magnitudes and (b) angles at different buses. The estimated error is highly dependent on the bus location. While no method produced the most accurate state estimates at every bus, overall using the more advanced techniques, such as the correlation method, improved the result accuracy further than using the methods of AV and NDF. The results suggest that bus 31 could be a candidate location to install a voltage transducer if the accuracy of the voltage estimate is not satisfactory.

Extremely large percentage errors of real power flow estimates were observed in some branches at certain time stamps. These error spikes were due to the connection of distributed generation close to the loads. Figure 4 shows the estimated real power errors in percentages on branch 59 for the total 2160 hours using the correlation method. At hour 336 the real generation output at bus 15 is very close to the demand at the same bus, resulting in almost zero real branch flows in branch 59. This gives a very large percentage error even if there is only a slight error in the estimate. Therefore using the percentage error as the only indicator of accuracy could give false indications as to the ideal locations to add new real-time measurements to reduce the errors, as was done in [9]. Figure 5 shows the errors in real power flow estimates expressed as percentages and absolute values (MW). Using the absolute values is one way to address problems caused by using percentages. Absolute errors are useful in determining the safety or operating margins that might be applied if using SE results within an ANM scheme.

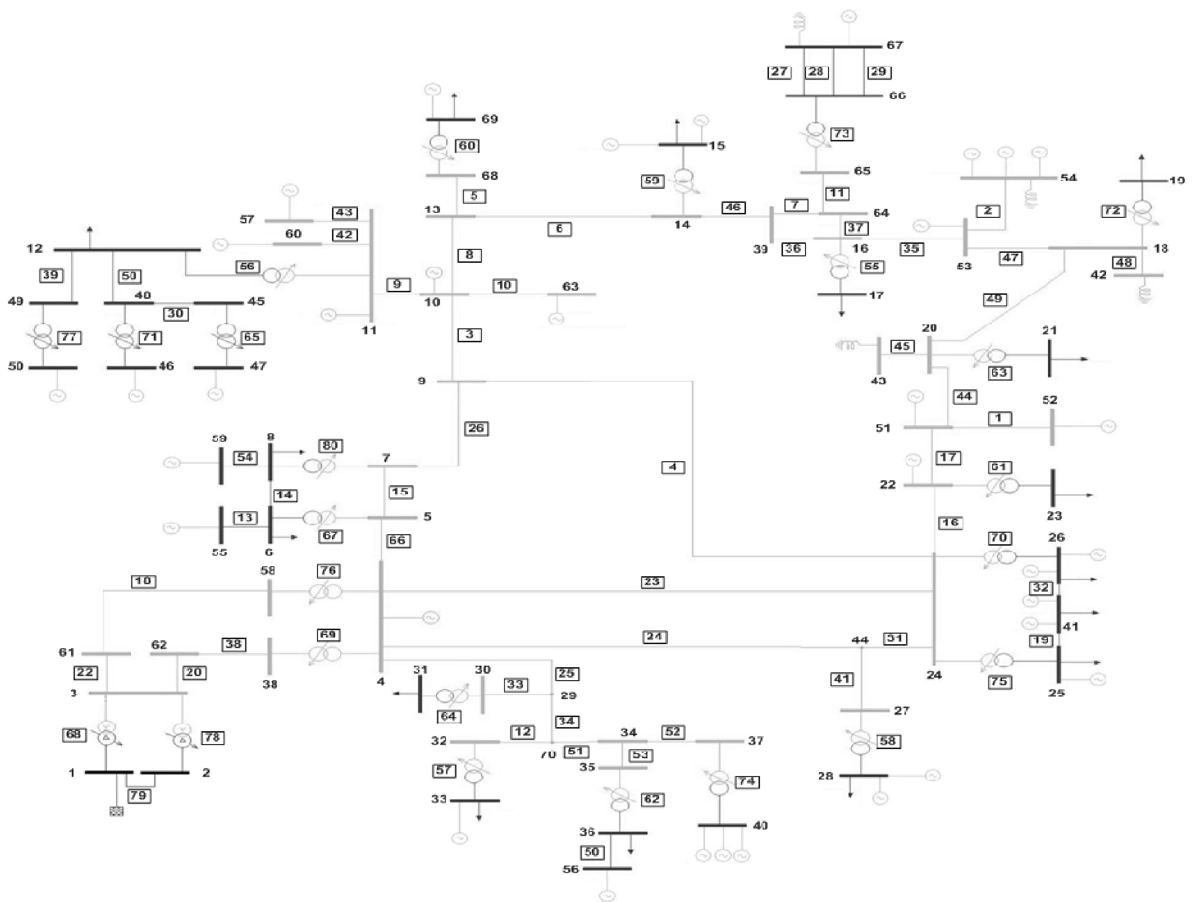

Figure 2: 70-bus 33 kV distribution network on Orkney Isles

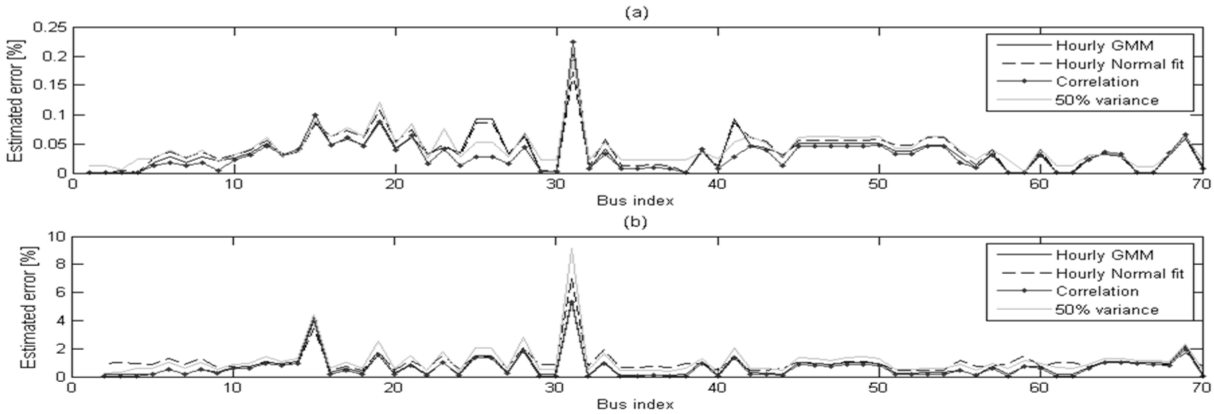

Figure 3: Estimated average percentage error of (a) voltage magnitude (b) angle state variables using different modelling methods

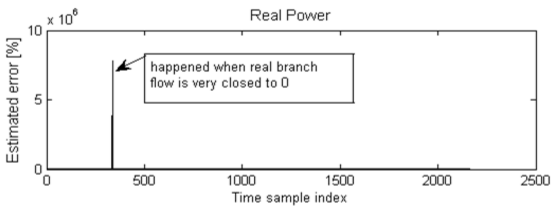

Figure 4: Estimated error percentage of real power flow estimates on branch 59 recorded in 2160 hours

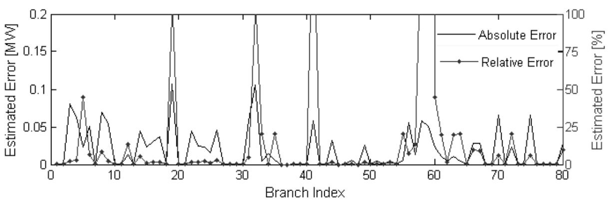

Figure 5: Errors of the real power flow estimates in percentage and absolute value

CONCLUSION

In this paper, four modelling methods were investigated to improve the accuracy of state estimation on the 33 kV network in Orkney, where a scheme has been established to actively control the generation of wind farms. The four modelling techniques include methods based on simple assumptions and normal distribution fitting, as well as more complicated methods like correlation and Gaussian mixture models.

The results showed that overall the errors of the state estimates were the smallest when the pseudo-measurements were modelled using the method of correlation, however, there was no method that produced the most accurate estimates at every location. A mixture of methods could be used to further improve the result accuracy. Moreover, extremely high error percentages were observed on some power flow estimates for branches that connect both generators and loads. When the branches experienced nearly zero power flow due to generation output closely matching demand, even slight errors in the pseudo-measurement resulted in large percentage errors in the branch flow estimates. In this condition the accuracy indicator expressed as a percentage would become inappropriate and give false information about the potential locations to install real-time measurements to reduce state estimation errors.

REFERENCES

1. Li, K., *State Estimation for Power Distribution System and Measurement Impacts.* IEEE Transactions on Power Systems, 1996. 11(1): p. 911-916.
2. Lu, C.N., J.H. Teng, and W.-H.E. Liu, *Distribution State Estimation.* IEEE Transactions on Power Systems, 1995. 10(1): p. 229-240.
3. Ghosh, A.K., D.L. Lubkeman, and R.H. Jones, *Load Modeling for Distribution Circuit State Estimation.* IEEE Transactions on Power Delivery, 1997. 12(2): p. 999-1005.
4. Mantisas, E., et al., *Modelling of Pseudo-measurements for Distribution System State Estimation*, in *CIRED*. 2008: Frankfurt. p. 1-4.
5. Do Coutto Filho, M.B., J.C.S. de Souza, and M.T. Schilling. *Generating High Quality Pseudo-Measurements to Keep State Estimation Capability*. in *Power Tech*. 2007. Lausanne.
6. Abur;, A. and A.G. Exposito, *Power System State Estimation: Theory and Implementation* 2004: Marcel Dekker, Inc.
7. Gjelsvik, A., S. Aam, and L. Holten, *Hachtel's Augmented Matrix Method - A Rapid Method Improving Numerical Stability in Power System Static State Estimation.* IEEE Transactions on Power Apparatus and Systems, 1985. 104(11): p. 2987-2993.
8. *Hourly Load Data Archives*. 2010, Electric Reliability Council of Texas.
9. Chilard, O., et al. *Distribution State Estimation Based on Voltage State Variables: Assessment of Results and Limitations*. in *CIRED*. 2009. Prague.