

Research summary: characterising the local strength of national grids

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The strength of an electrical power system varies at different points throughout the network. Worryingly, if too much power is withdrawn from an overly weak part of the system, a phenomenon called *voltage collapse* can occur, whereby a healthy-seeming power system suddenly collapses into a state of black-out. Understandably, this phenomenon makes operators deeply nervous as it is akin to Sudden Adult Death Syndrome for power systems. The present research proposes, and then validates, two new metrics for gauging the strength of the system at different locations. These new metrics could be used by an operator to monitor a system's health in real-time

This lay summary describes work in: P. Cuffe, F. Milano, "Validating Two Novel Equivalent Impedance Estimators", IEEE Transactions on Power Systems, Vol. 33, No. 1, pp. 1151-1152, January 2018.

Topic overview

Approach

Basic circuit theory shows that the maximum power deliverable to a load will occur when the load impedance matches the the feeding Thévenin impedance, and this concept underpins various approaches to appraising voltage stability at various points in a network. To date, though, it is unclear how to estimate the feeding Thévenin impedance at a point in a meshed network. The present work proposed and validated two new ways to infer an equivalent impedance from a system's admittance matrix. This matrix is a simple mathematical representation of the way powerlines connect together different substations.

The two new estimates for the feeding impedance were:

$$z_L^{\text{Sub}} = \text{diag}(\mathbf{Z}_{LL}) \quad (1)$$

and

$$z_L^{\text{Near}} = \min_{j \in L} z_{ij}^k, \quad i = 1, \dots, m \quad (2)$$

Alongside the two novel metrics, two established techniques for estimating an equivalent impedance were also trialled, to provide a comparative benchmark.

These two comparative estimators were:

$$z_L^{\text{Driving}} = \text{diag}(\mathbf{Z}_{\text{bus}}) \quad (3)$$

and

$$z_L^{\text{Topo}} = \sum \text{geodesic impedances} \quad (4)$$

considering the shortest path between the load and the nearest online generator

Test systems

To validate the quality of the different z_L equivalents, they were used to forecast the amount of load that can be served at a bus before voltage collapse is reached. Then, as a benchmark, continuation power flow techniques was used to directly calculate this threshold loading. A useful impedance estimator should be able to accurately forecast this threshold power. Empiric loadabilities were calculated for *every* load bus in each of nine test systems.

Results

The diverse quality of the predictions is shown in Table 1, which shows the *Mean Average Percentage Error*. For instance, considering every load bus in the `nesta_case30_ieee` system, the bus loadability prediction that was based on z_L^{Sub} typically deviated from the empiric value by 16%.

The novel z_L^{Sub} estimator consistently delivered the best loadability predictions. The z_L^{Near} estimator also performed well; it outperformed z_L^{Topo} , which doesn't properly account for the parallel nature of impedances within a meshed transmission system. Finally, Table 1 shows that z_L^{Driving} is wholly unsuited to predicting loadability limits.

A more granular view of the data is given in Fig. 1, which plots predicted versus empiric loadabilities at each load bus in the `nesta_case118_ieee` system. The clear linear trend for the z_L^{Sub} estimator is apparent, with most datapoints clustered tightly around the regression line.

Conclusion

The \mathbf{Z}_{LL} matrix was seen to contain information useful for bus loadability analysis. System operators could use this matrix to monitor the health of their

Table 1: Quality of loadability forecasts using each estimator

| System Name | z_L^{Sub} | z_L^{Near} | z_L^{Topo} | z_L^{Driving} |
|-------------------------------------|--------------------|---------------------|---------------------|------------------------|
| <code>nesta_case30_ieee</code> | 16 | 26 | 46 | 89 |
| <code>nesta_case39_epri</code> | 27 | 35 | 38 | 74 |
| <code>nesta_case57_ieee</code> | 12 | 14 | 40 | 80 |
| <code>nesta_case73_ieee_rts</code> | 14 | 28 | 37 | 52 |
| <code>nesta_case89_pegase</code> | 20 | 52 | 53 | 100 |
| <code>nesta_case118_ieee</code> | 7.7 | 25 | 39 | 47 |
| <code>nesta_case162_ieee_dtc</code> | 46 | 24 | 41 | 187 |
| <code>nesta_case189_edin</code> | 40 | 43 | 41 | 69 |
| <code>nesta_case300_ieee</code> | 24 | 28 | 38 | 49 |

system in real-time, to gain prescient warnings of when a bus might be reaching its loadability limit.

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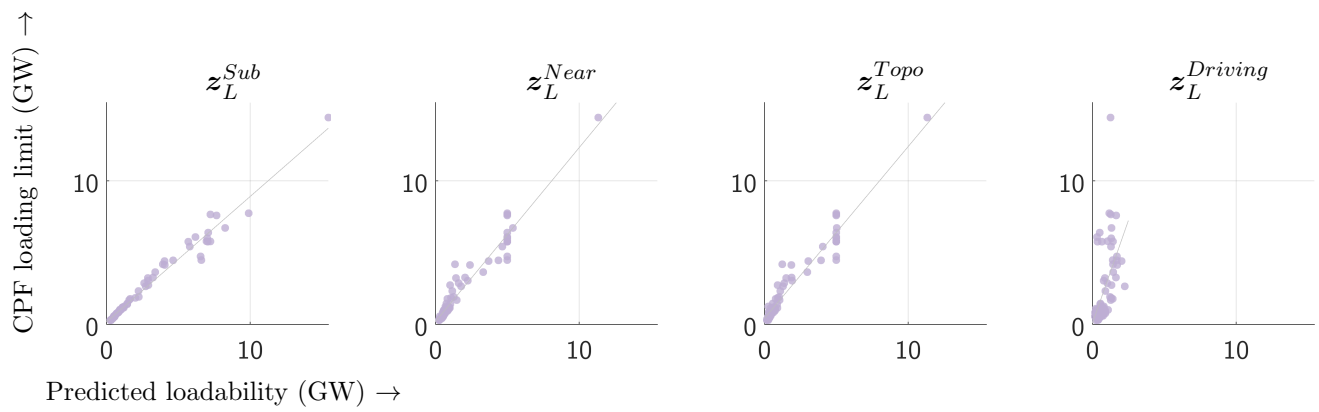


Figure 1: Four scatterplots showing the predictive efficacy of each of the four estimators: the two novel metrics are shown to the left, are seen to give the most accurate predictions `nesta_case118_ieee`