Dynamic Modelling of Active Distribution Networks

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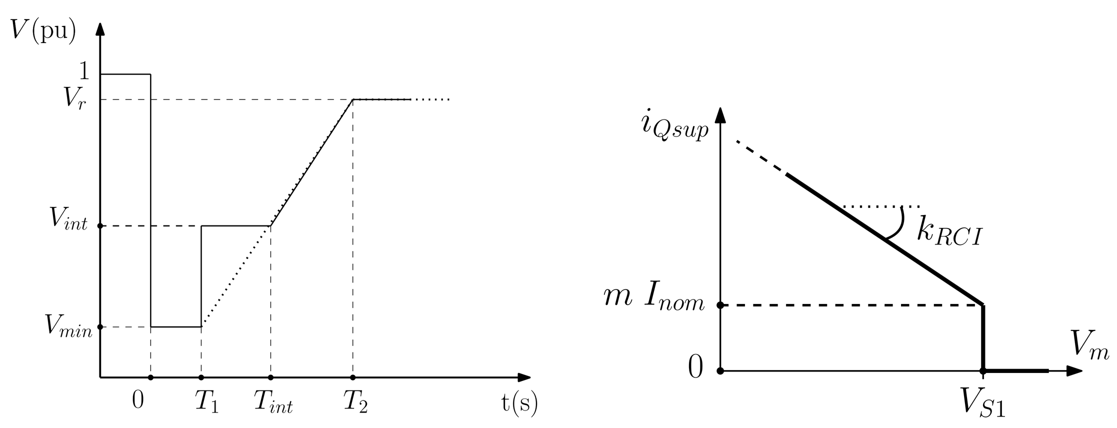
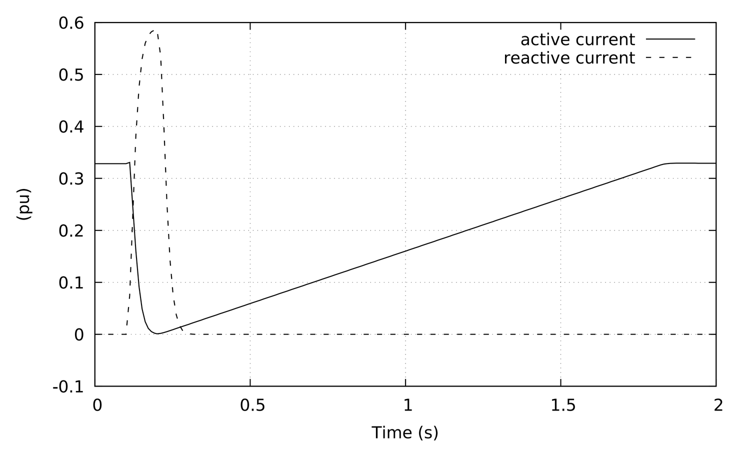
Motivation

- Power systems dynamics will be more and more influenced by Inverter-Based Generators (IBGs) connected to distribution networks through power-electronics converters
- It becomes urgent to account for the contribution of such Active Distribution Networks (ADNs) in power system dynamics studies
- A single, integrated model of both transmission and distribution systems is impractical
- Reduced dynamic models of ADNs are thus needed.

Inverter-Based Generators model

- A generic model of IBG has been developed; it focuses on the response of the unit to grid disturbances rather than a detailed representation of each physical components
- It is entirely parameterized and can be easily updated to accommodate a specific grid code





The active and reactive currents injection of an IBG in the event of a short-circuit on the transmission system is represented.

Part 1. Extracting one representative ADN model

Uncertain dynamic systems

One major issue when setting up a detailed ADN model lies in the uncertainty affecting the behaviour of its components. Their dynamic models involve parameters which are not known accurately. In this work, it is assumed that the individual dynamic behaviour of IBGs, loads, etc. can be reasonably well captured by a parameterized model, but the values of its parameters are uncertain.

Monte-Carlo Simulations

A well-known approach to deal with such uncertainty consists of performing Monte-Carlo (MC) simulations involving in this case random variations of the parameters. Thus, for given disturbances and operating points, a set of randomized time responses is generated. The next step is to extract from this large set one representative response. The parameters that yielded this response are used in the final ADN model.

Extracting a representative dynamic response

The approach consists in identifying $\boldsymbol{p}^{\star}$, the parameter instance which yields the response to which the other responses have minimal dispersion.

Objective function:

$$\min_{\boldsymbol{p}_i \in \{\boldsymbol{p}_1,\ldots,\boldsymbol{p}_s\}} \left\{ \sum_{\substack{\ell=1\\ \ell\neq i}}^{s} \sum_{j=1}^{d} \sum_{k=1}^{n} [P(\boldsymbol{p}_i,j,k) - P(\boldsymbol{p}_\ell,j,k)]^2 + \sum_{\substack{\ell=1\\ \ell\neq i}}^{s} \sum_{j=1}^{d} \sum_{k=1}^{n} [Q(\boldsymbol{p}_i,j,k) - Q(\boldsymbol{p}_\ell,j,k)]^2 \right\}$$

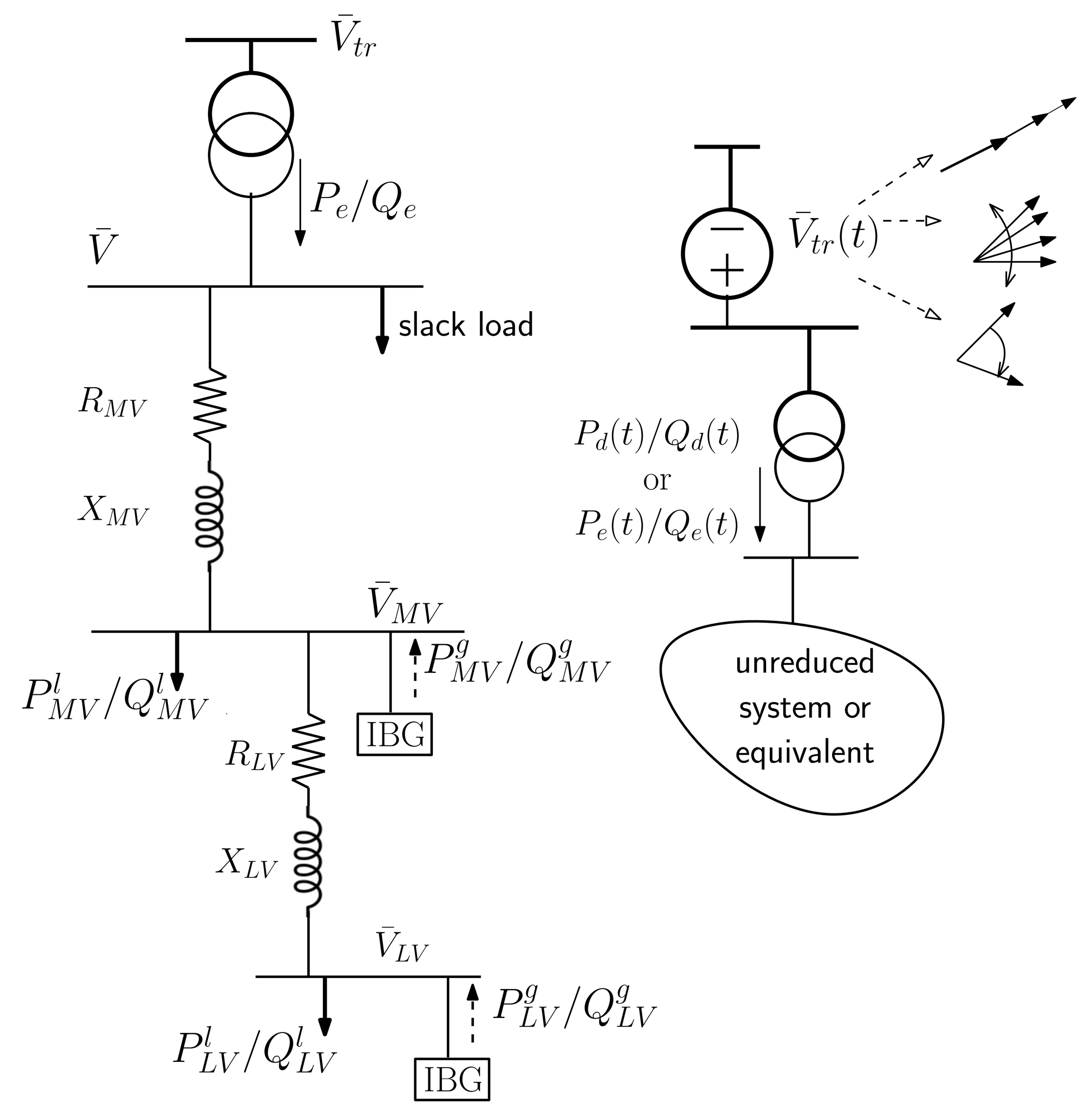
Part 2. Reducing the ADN model

Equivalent model features

Equivalents are reduced-order, anonymized mathematical models. They must be accurate enough to be used in large-disturbance analysis.
Besides accuracy, several other features are desirable:

1. be able to reproduce discrete events and discontinuities taking place in IBGs subject to large disturbances;
2. be compatible with standard dynamic simulation software.
3. be physically intuitive as far as possible (grey-box);
4. be easy to update when the operating point of the replaced distribution system changes;
5. be valid in a wide range of operating conditions.

Identification of the ADN equivalent



An equivalent valid for large disturbances should be derived from multiple "training" scenarios involving representative disturbances. The scenarios are obtained by replacing the transmission system with a time-varying voltage source $\bar{V}_{tr}(t)$.
The outputs of interest are the active and reactive powers entering the distribution grid.
The parameters of the equivalent are grouped in the $\boldsymbol{\theta}$ vector.
Let m be the number of training signals. For the j-th signal $(j = 1, \ldots, m)$, let us denote by:

$P_e(\boldsymbol{\theta}, j, k)$	the discrete-time evolution of the active power entering the equivalent system;
$Q_e(\boldsymbol{\theta}, j, k)$	the corresponding evolution of reactive power;
$P_d(j, k)$	the discrete-time evolution of the active power entering the unreduced system;
$Q_d(j, k)$	the corresponding evolution of reactive power,

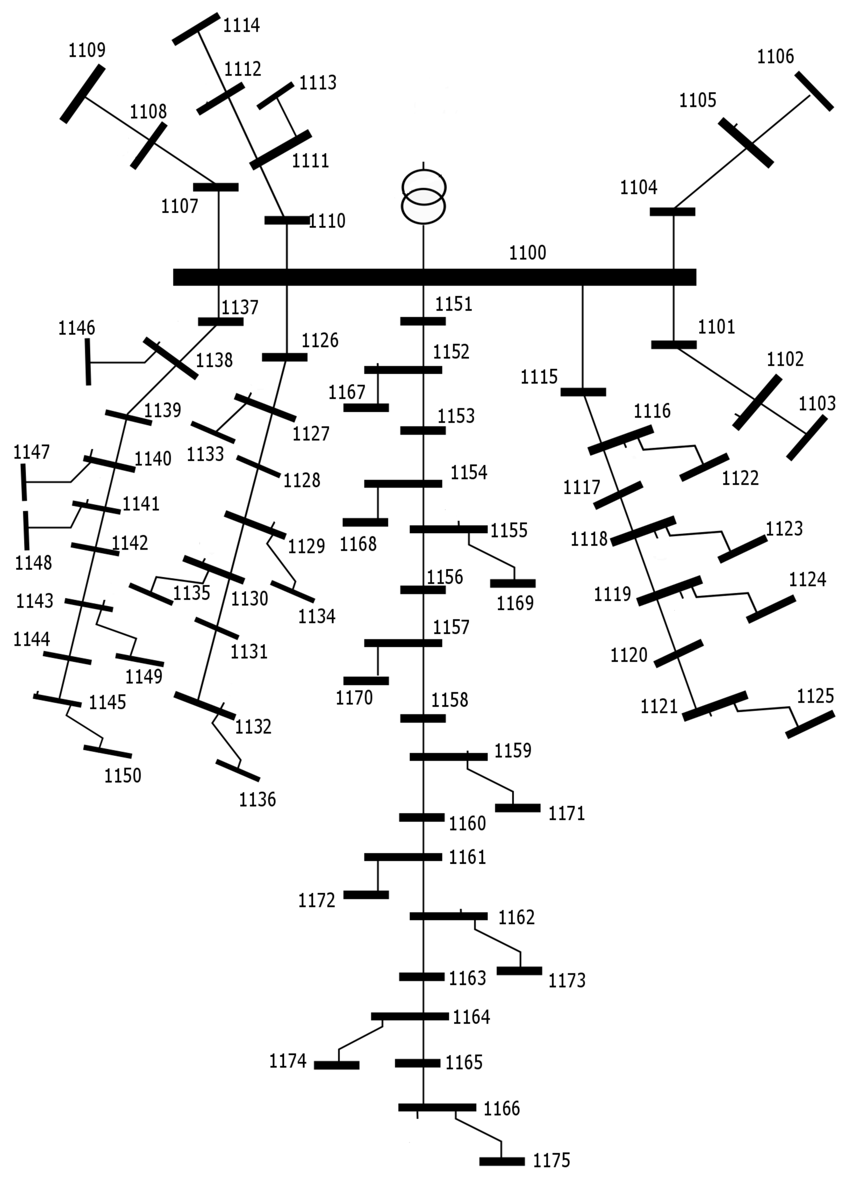
where k refers to the discrete times used by the time-simulation solver. The number of discrete times is denoted by n.
$\boldsymbol{\theta}$ is adjusted to match the m dynamic responses of the unreduced system all together in the least-square sense.

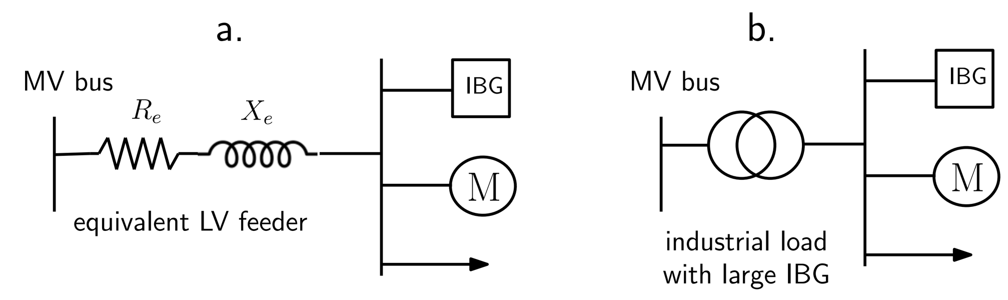
Objective function:

$$\min_{\boldsymbol{\theta}} \quad \varepsilon(\boldsymbol{\theta}) = \varepsilon_P(\boldsymbol{\theta}) + w\,\varepsilon_Q(\boldsymbol{\theta})$$
$$\varepsilon_P(\boldsymbol{\theta}) = \sum_{j=1}^{m} \frac{1}{n} \sum_{k=1}^{n} [P_e(\boldsymbol{\theta},j,k) - P_d(j,k)]^2$$
$$\varepsilon_Q(\boldsymbol{\theta}) = \sum_{j=1}^{m} \frac{1}{n} \sum_{k=1}^{n} [Q_e(\boldsymbol{\theta},j,k) - Q_d(j,k)]^2$$
$$\boldsymbol{\theta}^L \leq \boldsymbol{\theta} \leq \boldsymbol{\theta}^U$$

Test system

A 75-bus 11 kV distribution grid has been used in this study. Among the 75 MV buses 38 feed LV distribution grids hosting small IBGs without grid requirements (a). At the remaining 37 MV buses, the injection is modeled by an industrial load and a large IBG supporting the terminal voltage during a fault (b).

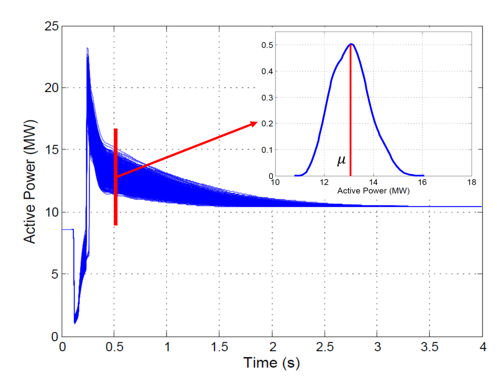


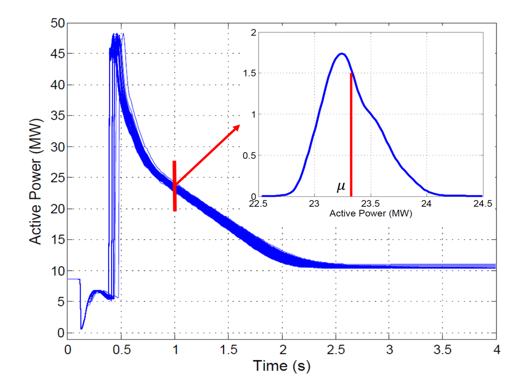


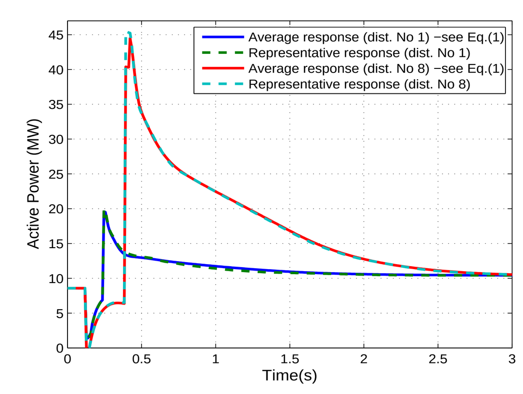
Simulation results

Part 1

Disturbances are applied on the transmission side. The set of active power responses entering the distribution grid are represented. The "best" representative responses are extracted and the corresponding ADN model is identified.

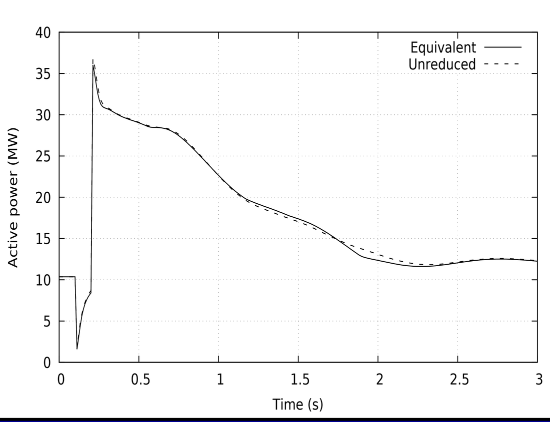


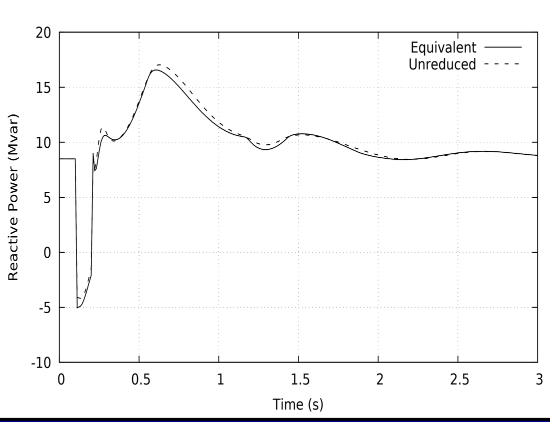




Part 2

The accuracy of the equivalent has been tested against an untrained signal and change of operating points.





Perspectives

The following extensions are currently considered :

- training signals involving phase jumps or frequency changes;
- validation tests with simulated measurement noise;
- identification of the parameters with less influence;
- Alternative "derivative-free" optimization method, with better control of the iterative procedure and lower use of random generation of parameter values.

Acknowledgement

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