# Model Reduction of Active Distribution Networks under Uncertainty

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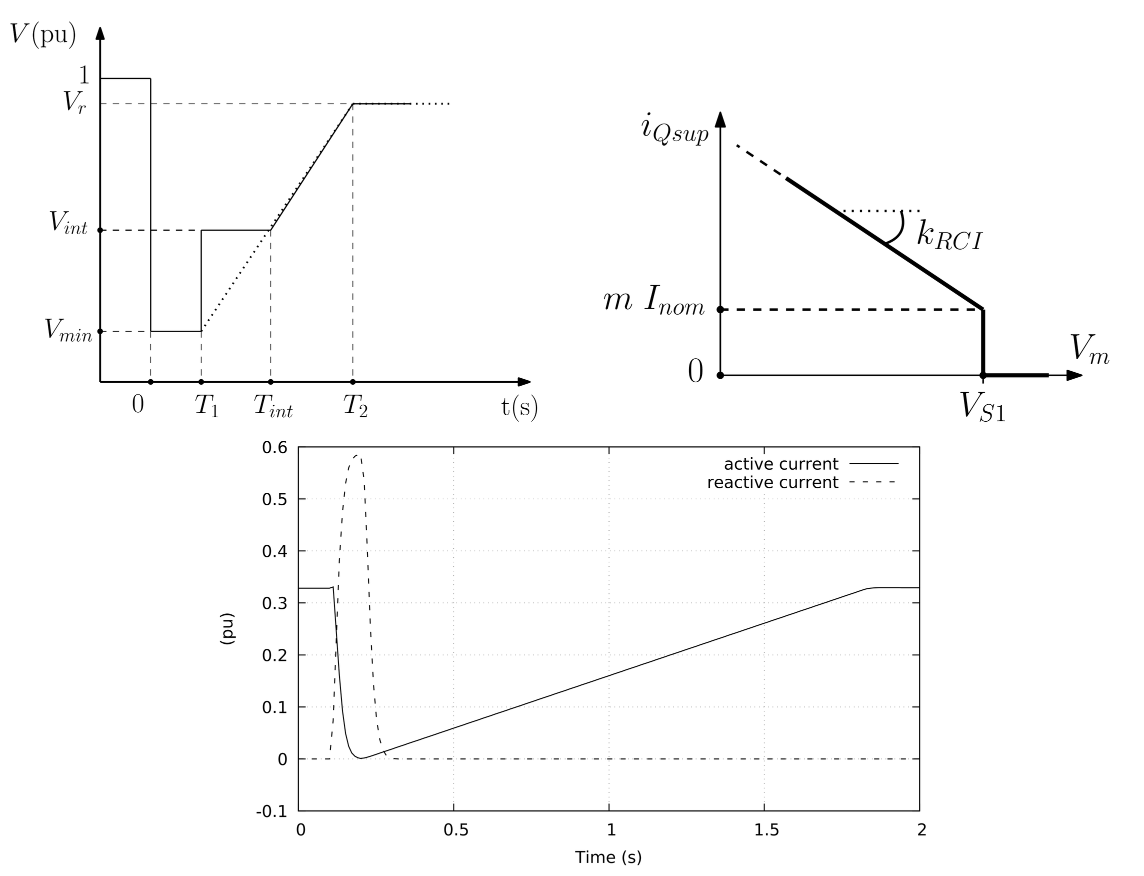
## Motivation

- Power systems dynamics will be more and more influenced by Inverter-Based Generators (IBGs) connected to distribution networks making the latter "active"
- It will be more and more important 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
- These equivalents are to be used by Transmission System Operators in the dynamic simulations of their systems subject to large disturbances

## 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 component
- It is entirely parameterized and can be easily updated to accommodate a specific grid code

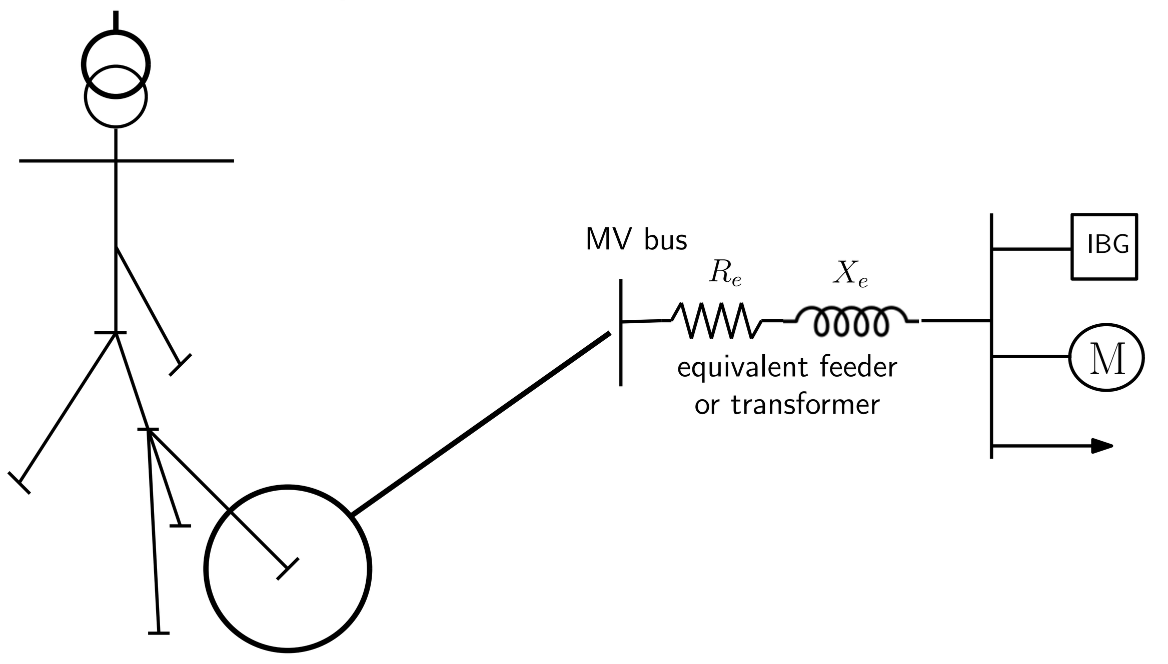



The active and reactive currents injection of an IBG in the event of a short-circuit on the transmission system is represented.

## Part 1. Analysis of the unreduced ADN model taking into account uncertainty

### Uncertain dynamic systems

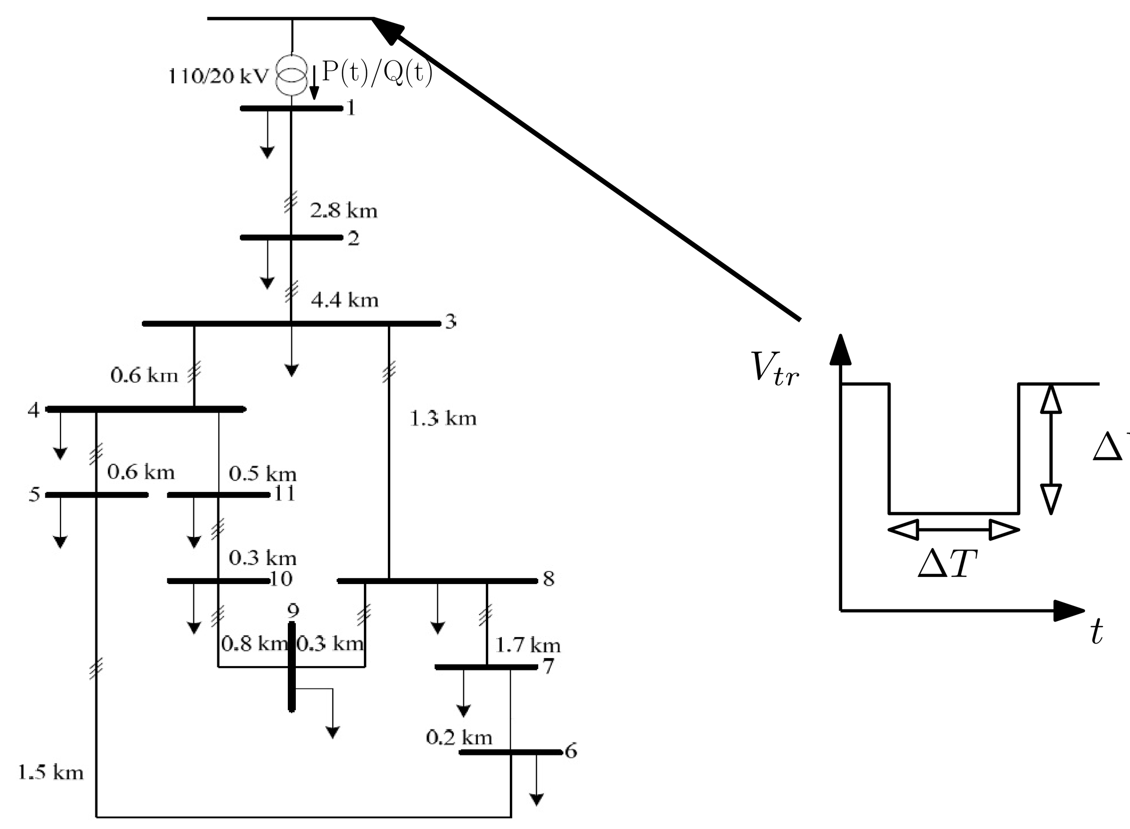
One major issue when setting up a detailed ADN model lies in the uncertainty affecting the behaviour of its components. Dynamic models involve parameters which are not known accurately. In this work, it is assumed that the individual dynamic behaviour of IBGs, loads, etc. can be correctly captured by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




### Monte-Carlo Simulations

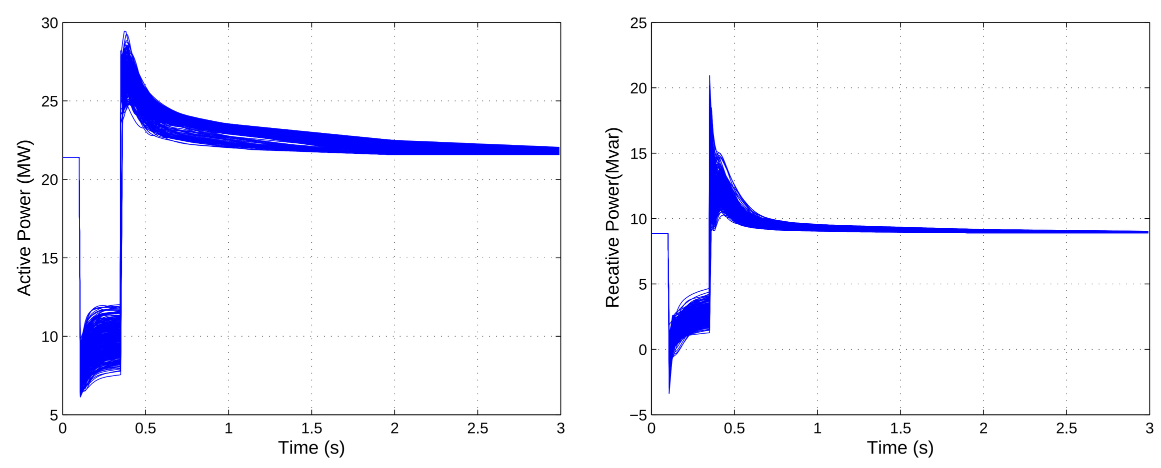
A well-known approach to deal with such uncertainty consists of performing Monte-Carlo (MC) simulations involving random variations of the parameters. Thus, for given disturbances and operating points, a set of randomized time responses is generated. The parameters are randomized from one MC simulation to another but also from one network bus to another.

## Example of simulation results




The outputs of interest are the active ($P(t)$) and reactive ($Q(t)$) powers entering the distribution grid.

Applied voltage dip : $\Delta V = 0.5$ pu, $\Delta T = 0.25$ s




## Part 2. Identification of the ADN equivalent

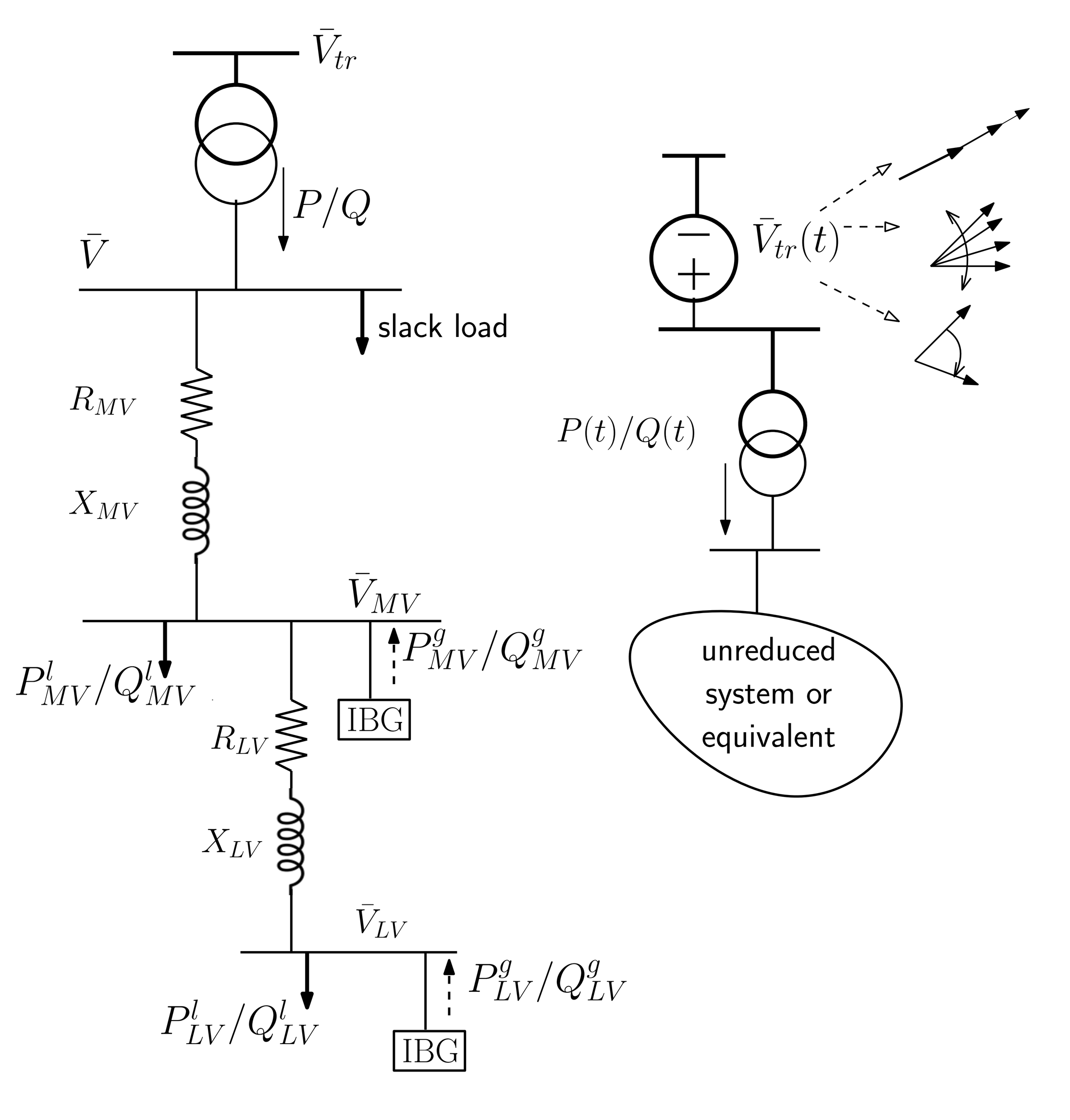
### Equivalent model features

Equivalents are reduced-order, anonymized models. They must be accurate enough to be used in large-disturbance analysis.

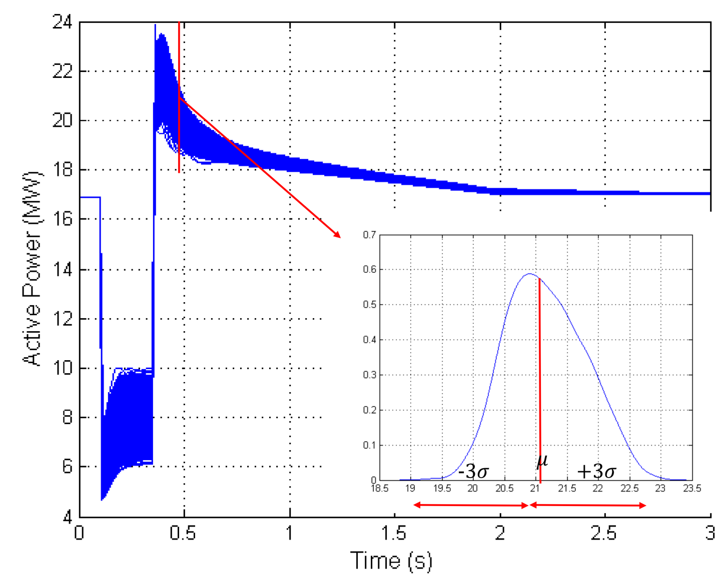
Besides accuracy, several other features are desirable:

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.

### Training of the ADN equivalent




**The dynamic equivalent is tuned to have its response** falling in time-varying confidence intervals obtained from the distribution of dynamic responses of the detailed (unreduced) model.




The equivalent is derived from multiple "training" scenarios involving representative large disturbances. Disturbances are simulated by replacing the transmission system with a time-varying voltage source $\bar{V}_{tr}(t)$.

The parameters of the equivalent are grouped in the $\boldsymbol{\theta}$ vector. For the disturbance $j$ and a discrete time instant $k$, let us denote by

$\bar{P}(j,k))$ the average of active power values entering the network at time k;

$\sigma_P(j,k)$ the corresponding standard deviation;

$P(\boldsymbol{\theta},j,k)$ the active power entering the equivalent;

The same applies to reactive power.

$\boldsymbol{\theta}$ is adjusted to minimize the objective function

$$\min_{\boldsymbol{\theta}} \quad F_r(\boldsymbol{\theta}) = \sqrt{F_P^2(\boldsymbol{\theta}) + w\ F_Q^2(\boldsymbol{\theta})}$$

$$F_P(\boldsymbol{\theta}) = \sum_{j=1}^{M} \frac{1}{N} \sum_{k=1}^{N} \left[ \frac{P(\boldsymbol{\theta},j,k) - \bar{P}(j,k)}{\sigma_P(j,k)} \right]^2$$

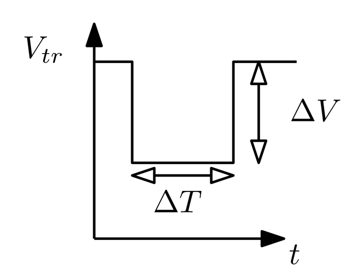
$$F_Q(\boldsymbol{\theta}) = \sum_{j=1}^{M} \frac{1}{N} \sum_{k=1}^{N} \left[ \frac{Q(\boldsymbol{\theta},j,k) - \bar{Q}(j,k)}{\sigma_Q(j,k)} \right]^2$$

$$\boldsymbol{\theta}^L \leq \boldsymbol{\theta} \leq \boldsymbol{\theta}^U$$

where $M$ is the number of training signals and $N$ the number of discrete times.

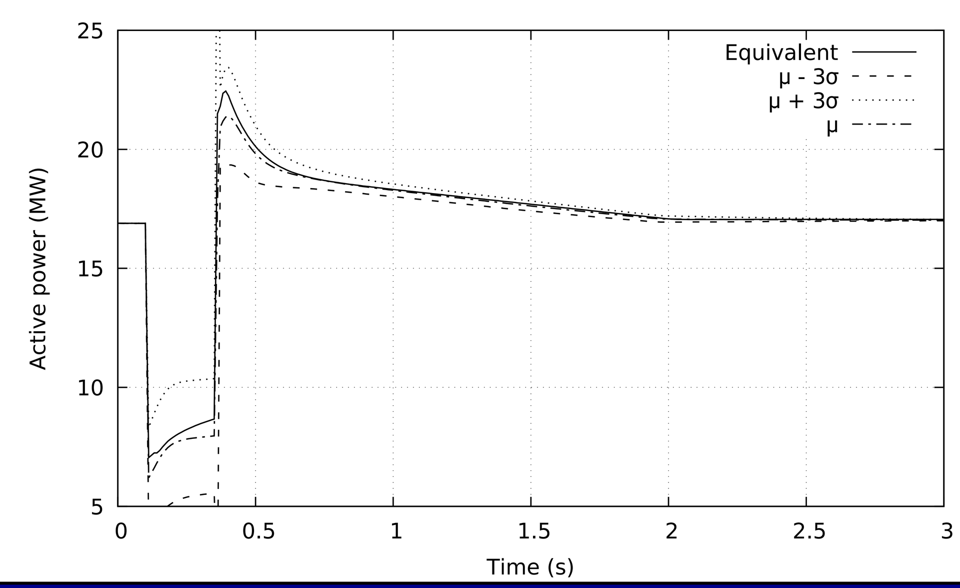
### Simulation results

**Training signals**




| Signal No | $\Delta V$ (pu) | $\Delta T$ (s) |
|---|---|---|
| 1 | 0.5 | 0.10 |
| 2 | 0.5 | 0.25 |
| 3 | 0.6 | 0.10 |
| 4 | 0.6 | 0.25 |
| 5 | 0.7 | 0.10 |
| 6 | 0.7 | 0.25 |
| 7 | 0.8 | 0.10 |
| 8 | 0.8 | 0.25 |

**Active power entering the equivalent in response to the disturbance No 7.**




### Perspectives

The following extensions are currently considered :

- testing accuracy in the presence of more complex variations of the transmission voltage;
- training on different operating points to account for changing load levels and weather conditions;
- recursive algorithm to select the optimal subset of training signals;
- 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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